Reparations for State Crimes as a Diffusive Norm*

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Abstract

This study applies extant theories on the diffusion of human rights to reparations for mass killing, and tests these theories using modeling techniques that account for the diffusive nature of reparations. I argue that reparations for state crimes are a rare, diffusive event, and that in order to understand their spread one must account for the conditional relationship between where and when diffusive processes are more likely. Drawing on extant theories of international policy diffusion and international law, I derive testable hypotheses regarding the diffusion of reparations for state crimes. These hypotheses are then tested on newly available data on reparations for the years 1971-2011 using Bayesian Weibull models that account for the underlying differences affecting the baseline likelihood and baseline hazard, respectively, of reparations, based on theoretical expectations. Primarily, I find that regimes with less political rights are significantly less likely to provide reparations. In addition, evidence from these theory specific hierarchical models suggests that more international reparations precedents are associated with increased time until reparations, whereas GATT/WTO membership and perpetrating regimes are associated with decreased time until reparations. These models also suggest that reparations become more likely over time, and can be used to identify countries that are inherently more likely to adopt them.

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The study of diffusion has produced an extensive number of exceptional articles (e.g. Simmons and Elkins, 2004; Solingen and Bórzel, 2014; Greenhill, 2010; Shipan and Volden, 2008). Yet, despite of the efforts of this impressive body of research, "we are nowhere near having a systematic, general understanding of how diffusion works" (Graham, Shipan and Volden, 2013, 675). Partly, this shortcoming results from differing conceptualizations of diffusion across different fields and shortcomings in the quantitative methods used to analyze these various conceptualizations. In this paper, I use the term "diffusion" to refer to a process in which "one government's decision about whether to adopt a policy innovation is influenced by the choices made by other governments" (Graham, Shipan and Volden, 2013, 675), and which "results in temporal and spatial *clusters* of policy reform" (Elkins and Simmons, 2005, 34). In addition to the different ways scholars understand and empirically model diffusive processes, the diffusion of human rights raises an additional problem; frequently in related panel time-series datasets, events are relatively rare (in the case of reparations, fewer than 20 cases).

A crucial aspect of human rights political processes is that many outcomes are the result of interactions between different levels of analysis, for example the international and the domestic (e.g. Elkins and Simmons, 2005; Chaudoin, Milner and Pang, 2015; Finnemore and Sikkink, 1998). While some of the factors governing reparations—such as the level of democratization or the country's GDP—are time dependent, meaning they vary over time, others—for example, geographic location or size—are very unlikely to change from one period to the next.

Focusing on reparations for mass killing as a diffusive political process, this paper employs a multilevel approach to understanding human rights policy diffusion. This approach accounts separately for where diffusion can actually occur, and what are the factors that might govern the diffusive process. In this, I follow the contention advanced by Graham, Shipan and Volden that "the future of policy diffusion research lies in uncovering the whens and wheres" (2013, 696), and—in using Bayesian approaches—compare methods of modeling diffusion that account differently for the wheres and the whens of this particular diffusive process.

There are several reason as to why reparations legislation should be modeled as a multilevel process. Firstly, as extant literature suggests, reparations for state crimes are a very rare event (de Greiff, 2006*a*), and their determinants are understudied, at least in political science. This suggests that most state crimes are normalized by means others than reparations, and that the process of (re)normalization might be influenced by historical and spatial dependencies that determine how likely a diffusive process is to actually occur. Time varying factors are therefore likely to have a different type of effect on the likelihood of reparations law for state-led atrocity—in this case mass killing, defined as the targeted killing of at least 1000 noncombatants by state forces[1]—compared with non-varying factors, such historical traditions and geographical conditions. For example, the inception of a democratic regime can produce new domestic and international pressures on leaders to award reparations for past abuses. In contrast, geographic proximities, e.g. if a country is surrounded by neighbors that previously adopted human right policies (Lutz and Sikkink, 2000), might expose countries to normative pressures or cultural similarities that increase the underlying likelihood of policy adaptation, but operate in a more indirect way.

Secondly, building on the premises of international policy diffusion proponents (e.g. Abbott and Snidal, 2000; Simmons and Elkins, 2004; Keck and Sikkink, 1998; Acharya, 2004), reparations legislation, if provided, is expected to involve different "levels" of political interactions, for example the international and the domestic. From this perspective, the time-dependent analysis of reparations would benefit from taking event hierarchy—i.e. different levels of political interactions, (see, e.g. Chaudoin, Milner and Pang, 2015)—into consideration. This is because domestic pressures might be more urgent for some regimes that seek to build legitimacy, while international pressures—which might facilitate the building of said

[1]This definition of mass killing (further elaborated upon below) draws on Ulfelder and Valentino (2008; see also Koren, Forthcoming) provides an empirical quantitative definition of an especially severe state-led crime.

legitimacy—are more likely to operate indirectly, e.g. through the actions of local norm entrepreneurs (Finnemore and Sikkink, 1998; Acharya, 2004; Greenhill, 2010).

Drawing on extant literature related to policy diffusion and international law, I accordingly seek to evaluate the above claims by deriving and testing hypotheses regarding the international diffusion of reparations. I specifically test these hypotheses by comparing two modifications of the Weibull model that account differently for the effect of time varying and non-time varying factors. In the first modification I include time-varying covariates in the main model, but allow the *intercept* to vary based on non-time varying factors (Gelman and Hill, 2007). In doing so, I allow each country to have a different baseline likelihood of adopting reparations, which is based on location and legal system, rather than treating this likelihood as being constant across all cases. In the second modification I again include time-varying covariates in the main model, but this time I allow the *shape parameter* of the model to vary based on non-time varying factors (see, e.g. Rouder et al., 2005). In doing so, I allow each country to have a different hazard—or "time-line"—until reparations are ultimately adopted, which again varies based on geographic location and legal system. I also conduct a separate Weibull analysis of only time varying factors as a baseline model to compare its estimate to those produced by the hierarchical models.

Primarily, I find that regimes that provide less political rights are significantly less likely to provide reparations. In addition, my hierarchical models, which are designed to better accommodate theoretical expectations, show that more international reparations precedents are actually associated with increased time until reparations, whereas GATT/WTO membership is associated with a decreased time until reparations. More important, perhaps, the estimates of the varying intercept models suggest that the global hazard for reparations increases over time, while the varying hazard models illustrates the effect of non-time varying factors on the hazard for each individual country, and allow us to how much variation exists between countries in the time until reparations are adopted, if ever.

Reparations as A Process of International Policy Diffusion

Reparations for mass killing are a relatively recent phenomenon. The modern origin of reparations for mass atrocities can be traced to the 1952 Luxembourg Agreement, in which West Germany agreed to pay reparations to the Jewish victims of the Holocaust. This agreement created an salient precedent, namely that reparations for former victims can play an important part in a new democracy's legitimization effort. The Luxembourg Agreement solved several pending problems for West Germany (Sebba, 1980). Firstly, the country experienced a surprising economic growth, and sought to enter foreign markets, some of which had financial elites that were not keen on the idea of trading with the former Third Reich (Teitl, 1997, 2006).

Secondly, in addition to the Nuremberg Trials, the victorious Western Powers also pressured West Germany to pay reparations, as did the newly founded State of Israel and the Jewish Claims Commission, or JCC (Laremont, 2001, 238). Thirdly, the US sought to re-align West Germany against the Soviet Block, and West Germany on its part wished to be included in the substantial financial package provided by the Marshall Plan. Fourthly, The process of turning West Germany into the bulwark of the West against the Iron Curtain necessitated ending denazification—the process of removing former Nazis and bureaucrats who served the Nazi regime from state institutions — which meant that through reparations these bureaucrats were given de facto absolution for their collaboration (Laremont, 2001, 241).

Despite the seeming benefits of reparations in the German case, however, it is unclear, *prima facie*, whether this policy actually represents a case of international diffusion. First, no international treaty on reparations with signatory states exists. International treaties and convention such as the Rome Statute and the Genocide Convention provide some framework for possible reparation-related court decisions, but—although under such binding treaties states may have the responsibility to prosecute crimes and to provide remedy—these are unlikely to be obligating when reparations legislation is concerned (Freeman and Pensky, 2012, 46-48). This situation becomes even more complicated in cases that precede the Rome Statues or in states that have not ratified it. In such cases, even prosecuting criminals might not necessarily be legally binding, let alone the right for compensation and remedy (Freeman and Pensky, 2012, 64).

Second, there is no exact definition of what kinds of acts justify reparations. The UN Guidelines on the Right to a Remedy states that "serious violations" deserve compensation, but these guidelines do not provide a definition for what constitutes a serious violation (The-UN-National-Assembly, 2014). Moreover, the definition of reparations under these UN Guidelines (compensation, restitution, rehabilitation, and satisfaction) makes any attempt to actually prosecute states for reparations all but unlikely to succeed. Third, even if a clear connection between a serious violation and the right to remedy through reparation is established, international law is only binding to states that have ratified the Rome Statues, and only for acts perpetrated after ratification. Although norms such as genocide prevention are so strong that they may involve intervention against the perpetrators and the use of hard international law, reparations remain a murkier issue.

The lack of hard, legally binding international legislation, however, does not necessarily prevent the diffusion of reparations by the way of policy imitation. Reparations are frequently provided in countries where leaders seek to rebuild credibility, and individuals lobby domestically by drawing on international norms. Since 1952, when the German government awarded compensation to Jewish victims of the Nazi regime, reparations have become an international norm on which non-state actors can draw (Keck and Sikkink, 1998; Finnemore and Sikkink, 1998; de Greiff, 2006*a*). Over time, international organizations and different international groups such as Amnesty International have become increasingly able to pressure regimes to provide reparations for their crimes, and promote reparations as being globally "appropriate."

To understand where reparations fall within the framework of international legalization, it is worthy to refer to the definition provided by Abbott et al., who use the term legalization to refer to "a particular set of characteristics that institutions may (or may not) possess. These characteristics are defined along three dimensions: obligation, precision, and delegation" (2000, 401). Obligatory legalization means "that states or other actors are bound by a rule or commitment or by a set of rules or commitments" (ibid., 401) that, "must be performed in good faith regardless of inconsistent provisions of domestic law" (ibid., 409). Precise legalization means, "rules unambiguously define the conduct they require, authorize, or prescribe" (ibid., 401). Delegated legalization means that, "third parties have been granted authority to implement, interpret, and apply the rules; to resolve disputes; and (possibly) to make further rules" (ibid.). International legalization thus refers to increased participation along a continuum of one or more of these dimensions.

Building on this premise, we can consider reparations to be a form of what Abbott and Snidal term "soft law." The notion of soft law refers to a legal policy that "begins once legal arrangements are weakened along one or more dimensions of obligation, precision, and delegation" (2000, 422). This is different from "hard law," which refers to "legally binding obligations that are precise (or can be made precise through adjudication or issuance of detailed regulations) and that delegate authority for interpreting and implementing the law" (2000, 421). This suggests two different, albeit similar, perspectives on reparations.

The first perspective asserts the importance of adaptation and learning in promoting the diffusion of reparations as a soft legal mechanism. For example, Simmons argues that states commit to treaties on rational grounds, which reflect their government's preferences, either because they sincerely believe in the treaty's goals or because they think that the treaty's benefits outweigh the risks of facing compliance pressures (2009, 64). However, once precedents for these soft legal obligations exist, they might cascade to become a standardized norm, even if for regimes that originally had no intentions of complying with these policies (Lutz and Sikkink, 2000; Keck and Sikkink, 1998). This cascade is the result of the "accompanying domestic, regional, and international enforcement mechanisms intended to pressure countries to comply with them," causing "regional political actors to transform their behavior" Lutz and Sikkink (657; see also Keck and Sikkink, 1998; Carpenter, 2015).

Building on these arguments in favor of norm cascade, learning, and adaptation, one might expect reparation precedents to produce a significant effect on the likelihood of a reparations law being passed in a given year. With more reparations precedents in place, a country can better learn of the potential effect of passing a reparation law, and hence lower potential costs of adoption. In addition, with more international reparation law precedents, a country is more likely to face pressures to adopt reparations as a means of renormalization (e.g. Murdie and Bhasin, 2011; Keck and Sikkink, 1998; Greenhill, 2010; Hughes, Krook and Paxton, Forthcoming; Hyde, 2011; Simmons, 2009). This suggests the following hypothesis:

- *H1: The time until the passing of a first reparations law for mass killing decreases with the number of international precedents of reparations for mass killing*

While international reparations precedents can produce an effect on a country's likelihood of passing a reparations law in a given year, some scholars have highlighted the importance of regional mechanisms in promoting norm cascades. These cascades can result from local activists "picking and choosing" norms that better fit extant conventions in their country of origin, as illustrated by examples from South East Asia (Acharya, 2004), North Africa (Solingen and Bórzel, 2014), and Latin America (Lutz and Sikkink, 2000). In balancing between employing radical ideas and ensuring that internationally imported norms are acceptable to local audiences, activists increase the chance that these norms become strong enough to produce political effects locally (Acharya, 2004). This in turn suggests that the diffusion of reparations, if exists, should be the result not (only) of international reparation precedents, but (also) of regional ones, which implies the following hypothesis:

- *H2: The time until the passing of a first reparations law for mass killing decreases with the number of regional precedents of reparations for mass killing*

The second perspective highlights the importance of reparations as a reconciliatory mechanism. For example, de Greiff argues that the essential advantage of reparations over other means of post atrocity renormalization is that "[f]or some victims, reparations are the most tangible manifestation of the efforts of the state to remedy the harms they have suffered. Criminal justice...is in the end a struggle *against perpetrators* rather than an effort *on behalf of victims*" (2006, 2). Moreover, reparations can also provide a less costly option for a regime seeking renormalization compared with the hard law option, which includes trials and prosecutions:

> Reparation programs at their best are administrative procedures that, among other things, obviate some of the difficulties and costs associated with litigation. These include long delays, high costs, the need to gather evidence that might withstand close scrutiny...the pain associated with cross-examination and with reliving sorrowful events, and finally, the very real risk of a contrary decision, which may prove to be devastating, adding insult to injury. A well-designed reparations program may distribute awards which are lower in absolute terms, but comparatively higher than those granted by courts. (de Greiff, 2006*b*, 459)

The lower costs offered by reparations, compared with "harder" options, might be especially useful for perpetrating regimes that remain in power after the mass killing ended. It is easy to imagine that leaders faced with the possibility of prosecution in either domestic or international courts would prefer atoning for their crimes by providing reparations to their former victims, even if this action risks infusing rather than diffuses social tensions (Gray, 2010). Moreover, even if the perpetrating regime is replaced, former functionaries might still become part of the new regime, especially in countries where there are relatively few trained bureaucrats (Laremont, 2001, 241). Perpetrating regimes that remain in power might therefore use reparations as a means of making amends with their previous victims, thus avoiding the "harder" option of prosecutions. This accordingly suggests the following hypothesis:

- *H3: Perpetrating regimes that remain in power after the mass killing campaign has ended will be associated with a shorter time until the passing of a first reparations law*

A related issue highlighted by scholars is the importance of liberalism and the role played by new democratic regimes following atrocities in renormalizing the relationship between the state and the citizens (e.g. Kaminski, Nalepa and O'Neill, 2006; Adhikari, Hansen and Powers, 2012; Gray, 2010; Cohen, 1995). There are several reasons why more liberal regimes are more likely to provide reparations. First, as Simmons argues, states might commit to treaties that are closer to their core beliefs (2009, 64). Therefore, one might expect liberal regimes to be more likely to adopt liberal policies, and to do so before everyone else. Although Simmons' argument pertains specifically to hard law regulations, there is no reason why softer policies should not also be adopted by regimes with similar core beliefs; if we treat international legalization as a spectrum rather than a binary space (e.g. "adopt/do not adopt), then less binding treaties allow liberal regimes to signal credibility at lower costs compared with no commitment at all. To quote Abbott and Snidal, "[l]egalization is a strategy through which actors pursue their interests and values; it also supplies a body of norms and procedures that shape actors' behavior, interests, and identities" (2000, 455).

Therefore, liberal regimes should be expected to be the first to adopt reparations for previous state crimes. Moreover, if liberal democratization is itself a diffusive process (Elkink, 2011; Lutz and Sikkink, 2000; Gleditsch and Ward, 2006), then we might expect it to be at least partly correlated with the diffusion of other liberal norms such as reparations. From a legal perspective, newly formed liberal democracies face strong pressures to address the wrongdoings of past repressive regimes (Adhikari, Hansen and Powers, 2012; Teitl, 1997). Such regimes also depend to a much greater extant on the approval and support of their own citizens, suggesting more pragmatic reasons to appease public opinion. Last, new liberal regimes might be especially dependent on international approval, which could be facilitated via adopting liberal policies (Teitl, 1997). This suggest the following hypothesis:

- *H4: More liberal democratic regimes will be associated with shorter time until a reparations law is passed*

Finally, Abbott and Snidal argue that soft law can be used as a substitute for hard law, although the two are not necessarily mutually exclusive (2000, 422). Rather, "[soft legalization] offers more effective ways to deal with uncertainty, especially when it initiates processes that allow actors to learn about the impact of agreement over time" (Abbott and Snidal, 2000, 423). As mentioned above, regimes might be oblivious to the long-term effects of soft legalization and choose to adopt it as a result of domestic pressures, or because they seek international legitimization.

Adopting any form of legalization allows the regime to enjoy the larger degree of autonomy and selectivity provided by the act of obligation. However, facing uncertainty during the transitional justice process, both in regard to hard laws—for example, by not being able to predict in advance what kind of punishment a post-atrocity tribunal might involve—and soft policies—for example, by not being able to predict how binding a reparations law might become over time, the regime might be willingly adopt the latter in the hopes of avoiding the former. Therefore, one might expect hard law solutions such as trials to be negatively associated to soft policies such as reparations. This suggests the following hypothesis:

- *H5: Criminal trials will be associated with an increased time until a reparations law is passed*

Variable Operationalization

The hypotheses posited above concern time-varying factors, that is, factors that might change from one year to the next. So, for example, no trials for perpetrators might be recorded in year t, whereas a trial might be recorded in year $t+1$. However, some conditions can remain constant over time, yet still influence the process by which a reparations law is passed. For example, Simmons argues that because in such systems treaties generally involve higher adjustments costs and more binding effect of precedents, "common law systems provide incentives for governments to go slow when it comes to treaty ratification, especially in the human rights area" (2009, 71).

Civil law systems, In comparison, might be more flexible and more forgiving in the long term, and hence more likely to be receptive of such legislation. Therefore, the historical formulation of the legal system of given country can shape the likelihood of reparations despite the fact that this historically defining event is highly unlikely to change over time. Hence, a country's legal tradition partly determines *where* reparations are more (civil law systems) or less (common law systems) likely, whereas the existence of time varying events such as criminal trials in a given year partly determines *when* reparations are likely.

Another important factor that can affect the likelihood of a given norm cascading is the country's geographic location and its neighboring states. Again, this indicator is highly unlikely to vary over time, unlike other events such as the number of regional reparations law precedents, which can increase from one year to the next. As a result, scholars observe a significant geographical variation in the diffusion of human rights legalization, with some regions—e.g. Latin America (Lutz and Sikkink, 2000)—being much more likely than others to experience events. Indeed, the importance of spatial dependencies has been highlighted by many scholars, who employ different approaches to account for them (e.g. Anselin, 2002; Zhukov and Stewart, 2013; Gleditsch and Ward, 2006; Darmofal, 2009). To account for these dependencies in the process of diffusion, and based on the importance of regional norms (Lutz and Sikkink, 2000; Acharya, 2004), I therefore include binary controls to account for world region.

Last, historical dynamics of social exclusion and ethnic divisions can also influence the likelihood of reparations, with more divided countries being perhaps less likely to award reparations (e.g. Pleskovic and Stiglitz, 2000). While ethnic divisions might vary over time, they are unlikely to change significantly within a country in the majority of cases, which results with ethnic divisions being coded as time invariant in most datasets (e.g. Roeder, 2011).

The universe of cases analyzed here included all state-led mass killing between 1970 and 2008 (a total of 68 cases in 48 different countries) obtained from "Assessing The Risk of State-

Led Mass Killing" written by Ulfelder and Valentino (2008).[2] Because some countries, e.g. Rwanda, experienced numerous mass killing events, I focused not on countries, but rather on specific mass killing cases. This provides an additional incentive to account for time varying and non-time varying accounts in separate equations to avoid heterogeneity concerns (Zorn, 2000). Ulfelder and Valentino (2008) define mass killing as "any event in which *the actions of state agents result in the intentional death of at least 1,000 noncombatants from a discrete group in a period of sustained violence*." Case years included all the years between the end of the campaign and 2011 (starting with the last year during which mass killing was coded), or the year when a first reparations law was passed.

To code my dependent variable (**First.Rep.Law**) I relied on the new dataset complied by the Transitional Justice Collaborative (Dancy et al., 2014). These data include reports on all reparation laws provided in response to state crimes since 1971. Because I am concerned with the time until reparations occur, I chose to focus only on the first reparations law that was passed, although some countries (e.g. Argentina) adopted several reparations laws.[3] If a first reparations law for mass killing was passed during a given year for one case, this case-year was given a value of one, zero otherwise. I relied on the same dataset to code whether major human rights trials—defined as "the use of domestic, foreign, or international courts of law with the aim to hold perpetrators criminally accountable for human rights violations" (Dancy et al., 2014)—took place during a given year (**Trials**), with a value of one assigned to a case-year during which trials were conducted, zero otherwise. This variable was used to test hypothesis H5.

To account for hypothesis H4 and measure a country's level of liberalism, I relied on the political rights index compiled by Freedom-House (2014). I additionally included Freedom House's civil liberties index for robustness purposes. Both indexes range from one (most free) to seven (least free). I relied on these measures because these indexes are less likely to be

[2] I did not include cases that the authors designated as "ongoing" in 2008.

[3] In one case, Sierra Leone, I coded reparations as occurring in 2000 rather than 1999, based on the original report used by Dancy et al. (see Conteh and Berghs, 2013).

affected by endogenous concern with the dependent variable compared with other datasets; and unlike other measures of democracy and rights, Freedom House data were available for all years analyzed in the data (1971-2011).

To test hypothesis H3, I coded the variable **Perpetrator**, which denotes whether the perpetrating regime remained in power during a given case-year, assigned a value of one, zero otherwise. To account for hypotheses H1 and H2, I coded indicators measuring the number of previous reparations for mass killing globally (**Rep.World**) and regionally (**Rep.Reg**), respectively, for each case-year.

I also included controls to account for alternative explanations to the ones hypothesized above. Firstly, I coded a binary variable measuring whether a country was part of the GATT or WTO during a given year (**GATT/WTO**), coded one, zero otherwise. I also included a binary control for whether a given case-year happened after 1990 (**Cold war**), coded one, zero otherwise. Lastly, I accounted for the possibility that the probability of reparations during a given year was affected by a country's population size or level of GDP. The data for population (**Ln pop**) and GDP per capita (**Ln GDPpc**) were obtained from "Expended Trade and GDP Data" coded by Gleditsch (2002 and 2013).

I also included a number of non-time varying covariates. First, I coded binary regional indicators for Africa, Asia, and Latin America, with Europe being the reference category. Following Simmons (2009), I further accounted for the difference between common (**Common.Law**) and civil (**Civil.Law**) law legal tradition (obtained from the "JuriGlobe" dataset, of Ottawa, 2014). Last, to capture ethnic heterogeneity I relied on the Ethnolinguistic Fractionalization (ELF) dataset (Roeder, 2011).

Methodology

Methodological Motivation

The fact that some political variables can "vary both across countries and over time" while others "may change slowly or not at all" (Chaudoin, Milner and Pang, 2015, 4) poses a challenge for diffusion scholars seeking to explain how and why policy clusters occur; or, as in the case discussed here, account for the effects of clustering when attempting to identify the factors governing a particular diffusive process. The sensitivity of time varying factors such as regime type, GDP, or membership in international organizations to diffusive pressures is likely to be higher than that of constant factors such as geographic location. Indeed, if one seeks, as Graham, Shipan and Volden highlight, to identify *when* a policy is more likely to be adopted, then time varying factors are crucial; the easiest way one can identify policy diffusion is by associating policy adoption with a significant change that occurred between one year and the next, e.g. the rise of a new democracy.

Yet, arguing that constant factors are irrelevant is clearly inaccurate; some policies cluster not only in time, but also in space. Partly, this can be explained if another wave of diffusion occurs simultaneously. For example increases in humans rights legislation in Latin America occurred simultaneously with a regional wave of democratization (Lutz and Sikkink, 2000). Yet, sometimes scholars observe policies that cluster in space, but not necessarily in time. For example, the provision of reparations for mass killing in Latin America is a phenomenon that occurred over the span of three decades, beginning with the end of mass killing in Argentina in 1983 (a first reparations law was passed in 1986), followed by El Salvador (mass killing ended in 1992, reparations the same year), Chile (mass killing ended in 1978, reparations in 1993), Peru (mass killing ended in 1992, reparations in 2001), and finally Guatemala (mass killing ended in 1996, first reparations law passed in 2003).[4] So although non-time varying factors might not have the same effect on when reparations are provided, they nevertheless influence—albeit to a different extant—*where* reparations were more likely to be provided.

One explanation for the lack of a consensus regarding how diffusion processes work is therefore the relative shortage in models that adequately account for the conditional relationship between time varying and non-time varying factors. This is especially important in cases where very few events are actually observed, reparations being one example. Lumping

[4] Another country, Nicaragua never provided reparations despite two mass killing campaigns that occurred in the country.

together a large number of potential explanatory indicators within an additive setup under the assumption that they all produce the same type of effect might generate false inferences (King and Zeng, 2001; Schrodt, 2014); and risks downplaying the importance of the conditional relationship between time varying and non-time varying indicators. To account for the whens and wheres of diffusion in a manner that fully accounts for the true processes and at the same time builds upon theoretical expectations, one must therefore estimate the likelihood that the effects of variables at one level of analysis will be conditional on the variables at the second level of analysis.

To do so, I rely on two Bayesian modeling solutions for small panel time-series data. Specifically, I assume that while time-varying factors influence the likelihood of a reparations law being passed in a given year, non-time varying factors influence the baseline likelihood of reparations in different countries. This approach better accommodates theoretical expectations, and—by allocating different degrees of influence to different factors based on these expectations—allows scholars to choose an empirical model that matches their particular theory. The resulting inference is therefore more accurate, and its interpretation more intuitive. This categorization is also more sensitive; it allows one to take into account specific factors highlighted by theoretical expectations and accommodate their effect in a more nuanced way compared with control-inclusive "kitchen-sink" models (Schrodt, 2014; Achen, 2000, e.g.).

These models have three main properties. First, they are parametric; each country's hazards is assumed to follow a two-parameter Weibull distribution (e.g. Box-Steffensmeier and Jones, 2004; Darmofal, 2009). The Weibull is a flexible form whose parameters correspond to the heuristics of scale, denoted here as λ; and shape, denoted here as ρ. Not that because I rely on the accelerated failure time (AFT) interpretation of these models, I also use the σ parameter, where $\sigma = \frac{1}{\rho}$. While I focus on the Weibull model, this approach can be generalized to other parametric distributions such as the exponential, Gompertz, and Gamma.

Second, these models are hierarchical, with separate model components for variability within a given case (time varying factors) and between countries (non-time-varying factors). In the first model described here, each country is accorded a unique intercept, but each reparations case shares the same shape parameter ρ with all the other cases. In the second model, each country is accorded a unique shape parameter ρ according to non-time varying factors, but a common underlying Gamma distribution describes the variability of these parameters. These approaches also account for historical path dependencies that spatial econometric models—which focus on the correlation of errors resulting primarily from geospatial clustering (e.g. Hoff and Ward, 2004; Gleditsch and Ward, 2006; Franzese and Hays, 2004)—might overlook.

Third, the method of parameter estimation and hypothesis testing is Bayesian. Researchers typically have several choices of methods in performing inference in non-hierarchical models with binary outcomes, including classical methods such as maximum likelihood (ML) and least squares. I choose Bayesian methods for the hierarchical models discussed below because of feasibility of estimation. Since the hierarchical Weibull models proposed here are outside the family of generalized linear models, Bayesian methods are usually preferred to perform inference (Gill, 2015; Gelman and Hill, 2007).

I choose to estimate time until reparations using the Weibull model for three mains reasons. First, the Weibull model is an accelerated time failure (AFT) model, meaning it is parametric (Box-Steffensmeier and Jones, 2004). This allows me to model the time until reparations based on non-time varying coefficients using a separate regression equation and identify units with respect to this time-line (hazard), which is awkward to do in semiparametric proportional hazard (PH) models such as the Cox (Carlin and Hodges, 1999; Zorn, 2000).[5]

Second, compared with other parametric models, the Weibull allows the hazard to monotonically change with respect to time (Box-Steffensmeier and Jones, 2004). Although the

[5]The use of the Weibull model also allows me to use a split population framework, see Supplementary Appendix.

monotonic assumption might be arbitrary when applied to a variety of social phenomena, it provides evidence as to whether the hazard of reparations is increasing or decreasing over time; and accommodates theoretical explanations concerning the factors that might influence this trend.

Last, while the use of Cox models to estimate reversion time in binary outcomes has become ubiquitous in political science, many studies on policy diffusion (e.g. Simmons and Elkins, 2004; Shipan and Volden, 2008; Darmofal, 2009) rely on the Weibull model to generate estimations or show robustness. From this perspective, the Weibull model is still one of the field's standard models, and its utilization here is in line with a large body concerned with the analysis of human rights diffusion. Moreover, while Cox models are used in applied work frequently, Weibull models often serve as the starting point for new methodological refinements in the methods arena of political science, owing partly to their relatively simpler estimation framework (e.g. Box-Steffensmeier and Zorn, 2001; Box-Steffensmeier, Reiter and Zorn, 2003).

Weibull Model With Varying Intercepts

For the ith year, reparations are either observed or not observed (censored), in which case $r = 0$. I assume that the likelihood of $r = 1$ follows a Weibull distribution, the hazard for which is modeled as follows:

$$h(t)_i = \lambda_i \rho t_i^{\rho-1} \tag{1}$$

Where $h(t)_i$ is the hazard of the ith individual at time t; λ is the scale parameter, which is modeled based on time-varying covariates (see below); and ρ is the shape parameter of the hazard, such that when $\rho < 1$ the hazard rate is monotonically decreasing, for $\rho > 1$ the hazard rate is monotonically increasing, and for $\rho < 1$ the hazard rate is flat. The survival function is thus modeled as follows:

$$S(T)_i = exp(-\lambda_i t_i^{\rho}) \tag{2}$$

Where T is the last year observed in the data for a post mass killing case. Correspondingly, the density function is modeled as follows:

$$f(t)_i = h(t)_\times S(T)_i = \lambda_i \rho t_i^{\rho-1} exp(-\lambda_i t_i^\rho) \tag{3}$$

The effect of time varying covariates is estimated via the scale parameter. Recall that I am using the AFT form of the Weibull model. This assumes that time can be modeled as a direct function of the covariates:

$$ln(t_i) = y_i = x_i\gamma + \sigma\epsilon \tag{4}$$

$$\sigma = \frac{1}{\rho} \tag{5}$$

$$\beta_i = -\frac{\gamma_i}{\sigma} \tag{6}$$

Where x_i are time varying covariate values, β_i is their corresponding coefficients, $\beta 0_{ij}$ is the intercept, which varies based on country j, and ϵ is the error term. To express Equation 3 in AFT form,I parameterize the scale parameter λ as follows:

$$\lambda_i = exp(-\frac{\mu_i}{\sigma}) \tag{7}$$

Where:

$$\mu_i = \gamma 0_{ij} + \gamma_i x_i \tag{8}$$

To assess whether a given covariate produces a reliable effect on the likelihood of a case experiencing reparations during a given year, the effect of the covariates in μ was assumed to be zero. The prior values for γ_i are thus as drawn from a normal distribution with a mean of zero and a relatively tight variance:

$$\gamma_i \sim \mathcal{N}[0, 0.01] \tag{9}$$

For the varying intercept Weibull, I employ a mixed effects framework that accounts for the effect of non-time varying covariates on the intercept, or the baseline likelihood, of a given case to experience reparations during a given year (Gelman and Hill, 2007). Because these non-time varying coefficients are set for each country rather than each post mass killing case, for a given country j the intercept values are drawn from a normal distribution as follows:

$$\gamma 0_{ij} \sim \mathcal{N}[\zeta_j, \tau_j] \tag{10}$$

$$\zeta_j = \delta_0 + \delta_j z_j \tag{11}$$

$$\tau_j \sim \Gamma[0.01, 0.01] \tag{12}$$

Where:

$$\delta_0, \delta_j \sim \mathcal{N}[0, 0.01] \tag{13}$$

Where z_j are non-time varying covariate values, δ_j their corresponding coefficients, and τ_j is the precision of the distribution.

Using this varying intercept framework thus allows me to nest the effects of non-time varying covariates within the Weibull duration analysis of time varying covariates as a separate equation. This has theoretical importance, because non-time varying coefficients are specific to each country and do not vary over time, whereas time-varying covariates are unique for each *case* and vary by the year. This suggests that non-time varying covariates produce a more indirect effect on the likelihood of reparations compared with that of time-varying factors, which additionally implies a conditional relationship between the two that remain unaccounted for by standard additive models.

Weibull Model With Varying Hazard

Alternatively, we can model non-time varying factors as influencing the *hazard* of reparations rather than their baseline likelihood. It is important to emphasize that this approach still relies on the two-parameter Weibull model rather than a three-parameter one (used by, e.g., Rouder et al., 2005; Zorn, 2000). Similarly to these models, the modification developed here provides a way of accounting for possible heterogeneity in the data, only instead of relying on random effects by country (Zorn, 2000) or case (Rouder et al., 2005), it employs a mixed effects (hierarchical) framework, which—by utilizing different regression equation for different "levels" of data—is more amenable to the empirical testing of theoretical implications (e.g. Gelman and Hill, 2007, 259, fn 4).

I let the shape parameter ρ vary by country j rather than remain constant, thus rewriting Equations 1, 2, and 3 as:

$$h(t)_i = \lambda_i \rho_{ij} t_i^{\rho_{ij}-1} \tag{14}$$

$$S(T)_i = exp(-\lambda_i t_i^{\rho_{ij}}) \tag{15}$$

$$f(t)_i = h(t)_{\times} S(T)_i = \lambda_i \rho_{ij} t_i^{\rho_{ij}-1} exp(-\lambda_i t_i^{\rho_{ij}}) \tag{16}$$

Again, I express these equations in AFT form, this time allowing the parameters ρ and σ to vary by country j. I thus rewrite Equation 4 as:

$$ln(t_i) = y_i = x_i \gamma + \sigma_{ij} \epsilon \tag{17}$$

$$\sigma_{ij} = \frac{1}{\rho_{ij}} \tag{18}$$

$$\beta_i = -\frac{\gamma_i}{\sigma_{ij}} \tag{19}$$

Correspondingly, the scale parameter from Equation 7 can be expressed as:

$$\lambda_i = exp(-\frac{\mu_i}{\sigma_{ij}}) \tag{20}$$

Where:

$$\mu_i = \gamma 0_i + \gamma_i x_i \tag{21}$$

Note that in this case $\gamma 0_i$ is assumed to be constant across all observations, while ρ_{ij} is drawn from a Gamma distribution with the following properties:

$$\rho \sim \Gamma[\kappa, \frac{\kappa}{exp(\zeta_j)}] \tag{22}$$

Where ζ_j is modeled similarly to Equation 11 above, and the hyperparamter κ is drawn from a uniform distribution:

$$\kappa \sim U[0, 100] \tag{23}$$

Results

To evaluate the hypotheses derived in the theoretical section, I relied on the two modifications of the Weibull model derived above—the varying intercepts (VI) and the varying hazard (VH) Weibull. For each of these modifications, two separate models were estimated. In the first set of models, only regional indicators were estimated within the non-time varying regression level. In the second set of models, the legal tradition and ELF indicators were additionally included. Apart from these models, I also report the estimates obtained from a baseline Weibull model, i.e. a model that did not include any non-time varying covariates. Each model was estimated in JAGS using the "zeros trick" approach (see Plummer, 2013, for more details). These estimates were calculated based on 201,000 Markov chain Monte Carlo (MCMC) simulations, of which 200,000 were discarded and 1,000 kept.

To assess the reliability of coefficient estimates I relied on 95% credible intervals (CI), which treat their bounds as fixed and estimate the parameter of interest as a random variable (Jackman, 2000). These CIs denote the range where 95% of the values of the posterior distribution for a given coefficient fall. If zero is not included within these 95% CIs, then a coefficient estimate was denoted as having a reliable effect on the time until reparations occur. In AFT models, negative coefficients mean that the coefficient *decreases* the time until an event occurs, while positive coefficients imply the time is *increasing*.

To assess model fit I relied on the Deviance Information Criterion (DIC) and the number of ideal parameters (pD) for each model. The DIC is a generalization of the to the Akaike Information Criterion (AIC), with smaller values denoting a better fitting model (Spiegelhalter et al., 2002). Like with the DIC, pD values correspond to a more parsimonious model. DIC values include pD estimates in addition to the expected value of the deviance of the posterior distribution. It is important to emphasize that these quantities should not be uses to interpret fit across models; the models utilized here rely on different approaches and employ different types of regression hierarchies based on theoretical expectations, which suggest that parsimony should not be used as a criterion for judging which model is preferred. However, these quantities could be used to estimate better fit between different specifications of each model, specifically the VI and VH models.

Table 1 shows the coefficient estimates of five Weibull models with different specifications. Most importantly, the **Political rights** coefficient is positive and reliable across all model specifications, confirming hypothesis H4.[6] All models thus suggest that more repressive and exclusive regimes are less likely to provide reparations, presumably due to the decreased domestic pressures for doing so.

Importantly, the differences between the hierarchical models, which are better designed to accommodate theoretical expectations, and the baseline model, are noticeable and substantively saliency. Firstly, Models (3), (4), and (5) suggest that more international reparation law precedents are associated with a *longer* time until reparations once the conditional relationship between time varying and non-time varying models is adequately modeled, which negates hypothesis H1. This suggests that diffusive mechanisms such as adaptation and learning discount reparations as a beneficial policy of transitional justice, compared with alternative options. The finding that perpetrating regimes are reliably associated with shorter time until reparations in Model (3) additionally supports this argument by suggesting that perpetrating regimes might use reparations to eschew pressures for stronger legislation. In addition, membership in the GATT/WTO is negatively and reliably associated with shorter

[6] These results hold in some control inclusive frequentist models, see Supplementary File.

Table 1: Standard, Varying Intercept, and Varying Hazard Weibull Model Estimates of Reparations for Mass Killing, 1971-2011

	Baseline	Region Only		Full	
		(Var. Int.)	(Var. Haz.)	(Var. Int.)	(Var. Haz.)
	(1)	(2)	(3)	(4)	(5)
Time Varying Covariates					
World rep.	0.439	0.192	0.436†	0.289†	0.249†
	(0.281)	(0.129)	(0.207)	(0.183)	(0.130)
Region rep.	0.107	0.148	-0.027	0.469	-0.126
	(0.481)	(0.256)	(0.289)	(0.484)	(0.149)
Perpetrator	-1.989	-0.943	-1.900†	-1.082	-1.047
	(1.709)	(0.673)	(1.004)	(0.915)	(0.774)
Pol. rights	1.966†	0.731†	1.704†	1.477†	1.139†
	(1.053)	(0.302)	(0.646)	(0.562)	(0.573)
Civil lib.	0.003	-0.141	-0.042	-0.564	-0.323
	(1.098)	(0.556)	(0.751)	(0.384)	(0.308)
Trials	-1.164	-0.504	-1.267	-0.718	-0.090
	(1.835)	(0.985)	(0.892)	(1.309)	(0.530)
Ln GDPpc	-1.019	0.158	0.359	-0.493	0.031
	(0.760)	(0.251)	(0.254)	(0.622)	(0.195)
Ln pop	0.770	0.115	0.584†	1.546	0.299
	(0.617)	(0.244)	(0.235)	(0.975)	(0.191)
GATT/WTO	-3.288	-3.288	-10.882†	-1.977	-12.457†
	(2.675)	(3.186)	(6.331)	(2.712)	(4.066)
Cold war	-0.864	-0.163	-1.712	-0.493	-0.697
	(2.485)	(0.814)	(1.238)	(1.294)	(0.462)
Intercept$_{tv}$	7.322	-	4.292	-	10.783†
	(7.997)		(6.780)		(3.240)
Non-time Varying Covariates					
L. America	-	1.378	1.328	0.304	2.329
		(3.082)	(1.070)	(4.658)	(1.659)
Africa	-	1.722	1.226	1.618	2.070
		(2.820)	(1.141)	(4.544)	(1.410)
Asia	-	3.674	1.227	3.726	3.123
		(3.051)	(1.066)	(4.402)	(1.703)
Civil Law	-	-	-	-0.170	0.999
				(4.021)	(1.406)
Common Law	-	-	-	-0.643	0.914
				(4.110)	(1.209)
ELF	-	-	-	-1.770	-1.775
				(5.513)	(1.754)
Intercept$_{ntv}$	-	1.923	-0.179	-4.841	0.367
		(4.095)	(0.988)	(6.703)	(2.582)
ρ	0.438†	2.624†	-	1.436†	-
	(0.158)	(1.444)		(0.825)	
σ	2.571†	0.517†	-	0.854†	-
	(0.890)	(0.293)		(0.333)	
DIC	2,328,254.00	2,328,393.00	23,280,245.00	2,328,280.00	23,280,171.00
pD	25.53	278.69	83.48	147.68	30.09
N-obs/reps.			1164/16		

Note: † denote whether zero was not included within the coefficient's 95% credible interval. Means for each posterior distribution are provided with standard deviations in parenthesis. Each model was estimated using 201,000 MCMC simulations, of which 200,000 were discarded as burn-in.

time until reparations in Models (3) and (5), suggesting that more international exposure could generate pressures for individual countries to provide reparations, which might confirm arguments concerning the normative diffusion of human rights through mechanisms such as the "boomerang effect" (Keck and Sikkink, 1998).

Another interesting contrast between the hierarchical models and the baseline model is the finding that the shape parameter ρ (as well as σ) in models (2) and (4) is not only reliable, but also that $\rho > 1$. Therefore, although the baseline model suggests that the hazard for reparations is monotonically *decreasing*—meaning that on average reparations become less likely over time—the VI models show that the hazard is in reality monotonically *increasing* over time. This suggests that, once we account for the conditional relationship between time varying and non-time varying conditions, reparations become *more* likely over time. Again, this illustrates one advantage of using inferential models that are more in tune with theoretical expectations.

The underlying clustering effect of non-time varying covariates is provided in Figures 1 and 2. These figures plot the 95% CIs by country for intercept and hazard values, respectively, for each case year. These plots have a different interpretation for VI and VH models. However, in both cases, for a constant intercept or a constant shape parameter, the plots would show all countries as converging on zero for all cases, i.e. all countries will an exactly equal baseline likelihood or hazard of experiencing reparations.

For the VI models, if a zero is not included in a given country's 95% CI, we can conclude that it was reliably (not) predisposed to experiencing reparations based on a combination of time-varying and non-time varying factors. So, for example, in Figure 1 (a), the intercept for Algeria (which provided reparations early on) suggests that, reliably, Algeria has a shorter time until experiencing reparations compared with the average country, based on the way time varying and non-time varying factors are modeled. Moving to Figure 1 (b), adding legal tradition and ethnolingual fractionazliation clearly improves our model estimates and helps identifying that some additional countries that did provide reparations relatively early on

(Nepal, Indonesia, Romania, and Sierra Leone) as also having a reliable baseline likelihood of experiencing early reparations, compared with the average country in the sample. Note that some other countries that provided reparations, perhaps most notably Peru, do not have a reliable baseline likelihood of experiencing early reparations compared with the average country.

For the VH model the interpretation is a little different. Here the quantity of interest is the variation in the shape parameter ρ values across different countries. Because these values are drawn from a Gamma distribution, a country cannot have a negative shape parameter. Instead, we look to see how much variation in the shape parameter exists between different countries. As Figures 2 (a) and (b) illustrate, countries that provided reparations early on—e.g. Algeria, Romania, Nepal, Indonesia—have practically no variation in the shape parameter, i.e. the model easily convergence on the true value of ρ. In comparison, countries that did not provide reparations, or that took relatively long to do so (e.g. Peru), have a (very) noticeable variation in shape parameter values, which is modeled based on the conditional relationship between time varying and non-time varying factors.

Figure 1: The Baseline Likelihood for Reparations By Country as A Latent Variable

(a) (b)

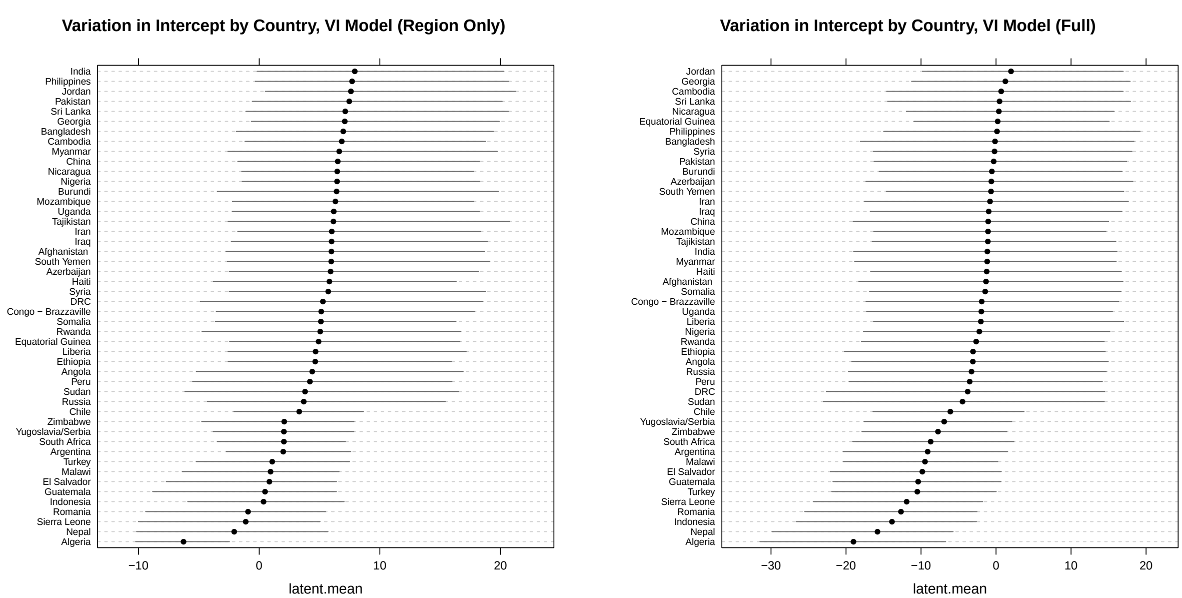
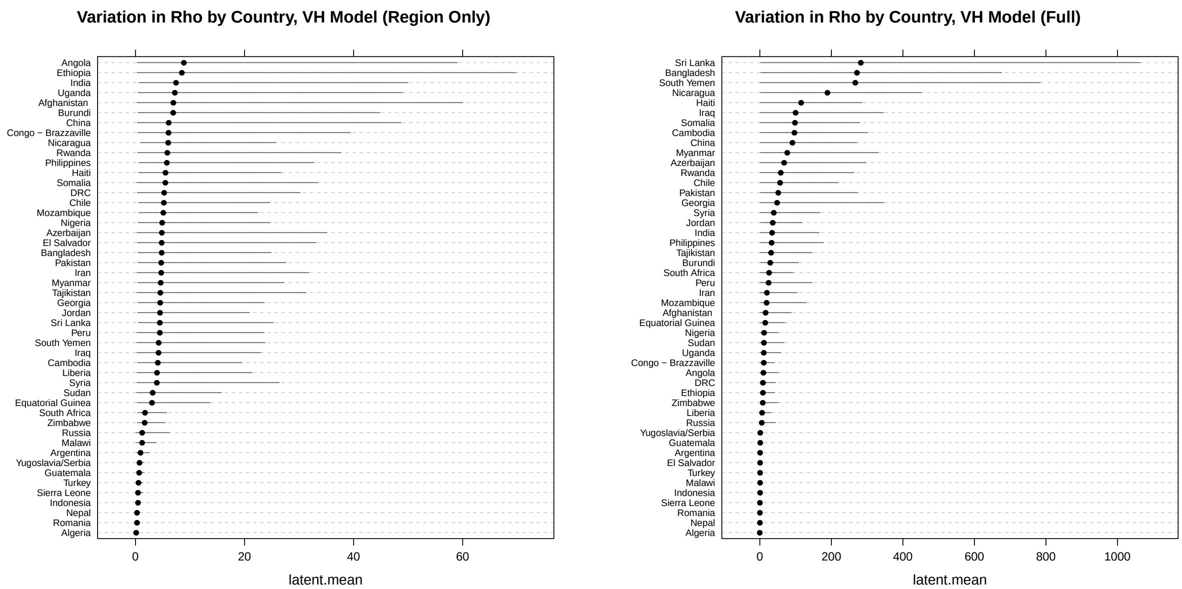


Figure 2: The Baseline Hazard for Reparations By Country as A Latent Variable

(a) (b)



Last, as can be clearly observed both for the VI and VH plots, adding legal system and ELF indicators has a noticeable effect on reducing the variation in intercept and shape parameter estimates, respectively, by country. This findings is supported by the lower DIC and pD values of Models (4) and (5) compared with models (2) and (3), respectively, which again suggest that models that additionally include these indicators provide a better fit for the data. This lends additional support to my decision to rely on hierarchical Weibull models to assess the effect of different indicators on the diffusion of reparations for mass killing as a diffusive process. By accommodating the conditional relationship between time varying and non-time varying factors, and by accounting not only for spatial (e.g. geographic location), but also *social* (legal system, ethnic divisions), our ability to model the diffusion of reparations is improved, even though these social covariates did not produce a statistically reliable effect.

Conclusion

This paper examined the global diffusion of reparations for state crimes (conceptualized as state-led mass killing) for the years 1971-2011. I relied on different modeling solutions that allocated different regressions to time varying and non-time varying factors to account for the conditional relationship between the two. In line with current theories on human rights policy diffusion and international law, regimes that provide less political rights were reliably associated with a longer time until reparations, presumably because they were less likely to face pressures to adopt reparations as a means of renormalization. However, by using hierarchical models I was able to identify additional factors that produced a reliable effect on the time until reparations, such as world reparation precedents (which were associated ith longer time until reparations); and GATT/WTO membership and perpetrating regimes (which were associated with shorter time until reparations). These models also suggest that—overall—the hazard for reparations worldwide is monotonically increasing. Last, I illustrated the advantages of using hierarchical models to simulate the effect of the conditional relationship between time varying and non-time varying factors on the baseline likelihood and baseline hazard of reparations by country. Importantly, the results of my analysis demonstrate that the reliance on these hierarchical models detect effects that remain uncovered when standard additive-setting regressions are employed.

Theoretical arguments regarding the spread of specific policies, and specifically the legalization of human rights, highlight the importance of learning, imitation, and adaptation as facilitating mechanisms of diffusion. While coercion can explain why some responses to human rights violation such as trials occur in the wake of atrocities, the focus on reparations as a "softer" form of legalization is less likely to occur by coercion, and therefore more instrumental in evaluating diffusive as defined by Elkins and Simmons (2005).

Reparations for severe state crimes are also a relatively rare phenomenon. The sample analyzed here included only 16 reparations for 68 cases of mass killing, or approximately 24%. As reparations are a softer form of legalization, and less likely to occur by coercion, the question of why regimes would choose to provide reparations requires taking into consideration a variety of factors and levels of interaction to explain the "whens and wheres" of reparations diffusion. I relied on modeling solutions that—by accounting for theoretical expectations and allocating different levels of influence to time varying and non-time varying factors—allowed me to do just that. In doing so, this paper complements other studies of international policy diffusion that provide a more nuanced understanding of the dynamics governing international diffusion and identifies locations where diffusion is more or less likely (e.g. Chaudoin, Milner and Pang, 2015). As illustrated in the Supplementary File, my main finding regarding the importance of political rights are robust to the reliance on these models.

My findings on reparations illustrate the advantages that regimes gain from adopting softer forms of legislation in lieu of harder forms. Indeed, trials did not appear to produce any reliable effects on the time until reparations, suggesting that regimes that adopted reparations did so not because they were coerced, but rather because they faced pressures from their constitutes, or because it was a preferred alternative. In other words, as Elkins and Simmons (2005) argue, leaders "pick and choose" the policies that best suit their interest, subject to international and domestic pressures (Chaudoin, Milner and Pang, 2015; Finnemore and Sikkink, 1998; Keck and Sikkink, 1998), historical legal constraints (Simmons, 2009), and regional convergence (Gleditsch and Ward, 2006). My findings are in line with theoretical expectations regarding the diffusion of reparations derived above using relevant bodies of research, which supports the argument that a better understanding of these processes can be gained relying on models that are more accommodating to specific theories.

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