From Gaddis to Mars:
The Decline of War Enters New Territory

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1. Introduction: The Decline of War Debate

John Gaddis famously argued that World War 2 was followed by a “Long Peace” (Gaddis 1986). This was, perhaps, an unfortunate coinage that can easily be misconstrued to imply an absence of war after 1946. However, Gaddis perceived relative, not absolute, peace and characterized the four decades following World War 2 as producing

> “…the greatest accumulation of armaments the world has ever known, a whole series of protracted and devastating limited wars, an abundance of revolutionary, ethnic, religious, and civil violence, as well as some of the deepest and most intractable ideological rivalries in human experience (Gaddis 1986).”

He expressed astonishment that the USA and the USSR had managed to avoid unlimited war for forty (now 76) years despite abundant provocations, some of which would probably have escalated into all-out war in earlier time periods.[1]

Multiple scholars built on Gaddis’ observation. (Mueller 1990) argued that the very idea of war has been progressively discredited over many decades as increasing numbers of people recognize its “stupidity” as a form of dispute resolution (Mueller 2021). (Lacina, Gleditsch, and Russett 2006) capped their major data collection effort with a finding of global decline in the “risk of death in battle” since World War 2, thereby extending Gaddis’ Long Peace story a further two decades and endowing it with a strong quantitative foundation.[2] They also introduced the idea of dividing global battle deaths by global population so that they could compare the risks of dying in battle faced by randomly chosen individuals alive at different time periods. (Human Security Centre 2006) focused on the post-cold-war period and looked beyond battle deaths, finding that military coups, genocides and the number of armed conflicts also declined, although the last of these trends has subsequently been reversed (UCDP n.d.). (Goldstein 2012) found that the post-World-War-2 (uneven) decline in battle deaths has been accompanied by shrinkage in the geographical area afflicted by war.

(Pinker 2012) expansively considered violence as a whole, finding across-the-board reductions in all violence forms he managed to analyse.[3] Yet Pinker’s case for the decline of *war* specifically concentrated narrowly on Gaddis’ Long Peace and the

[1] (Chamberlin 2018) argues that this focus on great power conflict obscured the proxy wars these powers sponsored throughout the Cold War. This is a reasonable observation but, as we shall see, is even more true of the 19th century than it is of the Cold War.
[2] However, the post-World War 2 decline in battle deaths is not monotonic.
[3] Again, these declines are not necessarily monotonic.

subsequent post-Cold War period, the latter of which he designated as the "New Peace".[4]

(Pinker 2012) also ventured beyond a litany of violence-decline statistics and introduced Lewis Fry Richardson's (Richardson 1960) discovery of the fat-tailed distribution of war sizes, usually modelled as a power law, into the decline-of-war discussion:

> "The thick tail of a power- law distribution, which declines gradually rather than precipitously as you rocket up the magnitude scale, means that extreme values are *extremely unlikely* but not *astronomically unlikely*. It's an important difference…. I hardly need to point out the implications for war. It is extremely unlikely that the world will see a war that will kill 100 million people, and less likely still that it will have one that will kill a billion. But in an age of nuclear weapons, our terrified imaginations and the mathematics of power- law distributions agree: it is not astronomically unlikely." (Pinker 2012)

(P. Cirillo and Taleb 2016), (Clauset 2018) and (Braumoeller 2019) subsequently build the fat-tail property in the distribution of war sizes into a critique of the decline-of-war thesis without actually disputing the claim of (Lacina, Gleditsch, and Russett 2006) that battle deaths have declined since World War 2.[5] Their central idea is that if truly massive wars are extremely, but not astronomically, unlikely then the absence of such wars after World War 2 may result merely from a run of relatively lucky draws from an unchanging distribution of war sizes. Further decades without truly massive wars would be needed before we could reject at a conventional significance level a hypothesis of an unchanging distribution of war sizes applying both pre and post-World War 2. Thus, a downward trend in battle deaths is compatible with a stable, but fat-tailed, war-size generating mechanism.

(Clauset 2018) and (Braumoeller 2019) both fit power laws to war-size data[6], first for the period from 1816 through World War 2 and, second, for the post-World War 2 period. Neither researcher rejects a null hypothesis that the same slope coefficient (in a log-log plot) governs both their pre-war and the post-war estimated power laws and both interpret this finding as demonstrating continuity between the pre and post war periods.

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[4] (Pinker 2012) does considers European war all the way back to 1400 but finds ups and downs over the subsequent seven centuries: "The career of organized violence in Europe, then, looks something like this. There was a low but steady baseline of conflicts from 1400 to 1600, followed by the bloodbath of the Wars of Religion, a bumpy decline through 1775 followed by the French troubles, a noticeable lull in the middle and late 19th Century, and then, after the 20th- century Hemoclysm, the unprecedented ground- hugging levels of the Long Peace." (Gat 2008) champions of the thesis that war has declined for many centuries, however we will not engage with Gat's formidable tome here since we use data going back only to 1800.

[5] Hereafter, we set aside Cirillo and Taleb (2016), as their dataset has not been publicly peer reviewed and their analysis explicitly does not consider change points or time series analysis.

[6] They both use the Inter-State War data of the Correlates of War project (Sarkees and Wayman 2010).

(Cunen, Hjort, and Nygård 2020) and (Fagan et al. 2020) both use change-point detection methods designed for fat-tailed distributions that, while differing substantially in their specifics, deliver evidence for a decline of war that took hold some time after World War 2. (Cunen, Hjort, and Nygård 2020) identify 1950 as the best candidate for a switch to a downward trend. (Fagan et al. 2020) also pick out 1950 but, in addition, find evidence for change at 1910 and possibly for the 1830's, 1930's and 1990's. (Spagat and van Weezel 2020) did not use a general change-point detection method but, rather, considered only 1945 and 1950 as possible change points. They found evidence for a downward shift in the war-size distribution starting at 1950 but only when war sizes are measured by battle deaths per 100,000 of world population. (van Weezel 2020) uses Bayesian methods to estimate a probability of at least 0.66 that the risk of dying in battle decreased after 1947.

The literature, in short, is divided on the grand question of whether war is in decline but united on the need to integrate the fat-tailed nature of the distribution of war sizes into any analysis of the question. Note, further, that the papers described in the preceding three paragraphs focus only on numerical data, making little or no effort to connect their quantitative analysis with historical contexts.

Our paper advances the case for the decline-of-war thesis in four new dimensions. First, we introduce the Project Mars dataset (Lyall 2020b) into the debate and argue that it provides a far more appropriate basis for analysis than does the workhorse database of the decline-of-war critiques: the Inter-State War data of the Correlates of War (COW) Project (Sarkees and Wayman 2010). Second, we marshal the work of cold-war historians to identify the Korean War as a key turning point in the last two centuries of war history, setting the stage for a decline of war within a still dangerous and violent world. Third, we explain important, but not widely appreciated, weaknesses in the decline-of-war critiques of (Clauset 2018) and (Braumoeller 2019). Along the way we find that many fat-tailed distributions fit war-size distributions as well as power laws do, i.e., there is no reason to privilege power laws in our decline-of-war discussions. Fourth, and most important, we present our own analysis of the Mars dataset that strongly suggests decline of war since the Korean War. We conduct our analysis using both null hypothesis significance testing (NHST) and a Bayesian framework and we measure war sizes both by counts of the total number of combatants killed in action (KIA) and by KIA counts per 100,000 of world population. In addition, we begin by working with all the data but progress to considering only wars with KIA counts above a series of progressively higher minima, i.e., wars with KIA great than 2,000, wars with KIA greater than 3,000 etc.. When using all the data we find, independent of treatment, extremely strong evidence for a large post-1950 slowdown in the arrival rates for new wars. When we restrict attention to just wars with KIA counts above some threshold, S, then the analysis becomes nuanced, as will be explained below. But the evidence still points to slowdown and does so strongly when we adjust KIA counts for world population.

2. Important New Data

Project Mars (Lyall 2020b) provides data on many variables for what the project determined to be all 252 conventional wars waged across the globe between 1800 and 2011. The rigour of the rigour of the coding work is underscored by a further list of 90 "edge cases" and their reasons for exclusion.[7] We use only the variables for low and high estimates of KIA and the start years for each war. KIA includes just military personnel killed in battle, a concept that seems to be identical to that of "battle deaths" for COW. We argue here that Mars is such a major advance over COW that it necessitates a fresh exploration of the decline-of-war question.

Mars' first main advantage is that it is a truly global database of wars over the last two centuries. In contrast, COW Inter-State is profoundly Eurocentric.[8] COW Inter-State includes 19th and early 20th century wars only if they are between two belligerent powers that were recognized at the time as bone-fide States by either France or the UK (Correlates of War Project, 2016).[9] This might seem like an innocuous technical assumption but it embeds a 19th century imperial view of much of the non-European world as ungoverned territory available for the taking. (Elkins 2022) explains that influential 19th century British historian Robert Seeley, writing on India:

> "…suggested that the notion of conquest was misplaced. India was not a nation with a political community; rather, with the fall of the Mughal Empire, the subcontinent was home to a Hobbesian state of anarchy. 'It remains entirely incorrect to speak of the English nation as having conquered the nations of India…India can hardly be said to have been conquered at all by foreigners,' Seeley insisted, 'she has rather conquered herself.'

Due to the supposed dearth of legitimate political authority outside of Europe, COW contains 16 purely European wars, 12 wars between a European and a non-European country and just 10 wars without European participation between 1816 and 1913.[10] The "Great Game" and "scramble for Africa" notwithstanding, COW lists 0 wars in both South Asia and Sub-Saharan Africa. Thus, the COW Inter-State war data is compromised by a colonial perspective which, paradoxically, erases 19th

[7] The appendix contains more detail on the Mars database.

[8] COW Inter-State dataset is used extensively in the quantitative IR field with (Clauset 2018) and (Braumoeller 2019) relying on it, respectively, exclusively and heavily. Different issues would arise for other COW datasets, but we confine our critique to the data they actually use rather than to data they might have used.

[9] After their founding, recognition by the League of Nations and, later, the UN became another pathway into the dataset. Additionally, there have been inconsistencies introduced throughout the lifetime of the dataset, further complicating the coding (K. Gleditsch et al. 2004).

[10] We treated the Ottoman Empire as part of Europe for this calculation.

century colonialism.[11] Worse, COW applies the same criterion of non-recognition by the UK and France to exclude several non-colonial wars with clear relevance to the decline-of-war debate, including the US, Russian, Spanish and Chinese civil wars.[12] Dropping the requirement for British/French validation is the main reason why Mars raises the number of belligerent groups, relative to COW Inter-State, from 95 to 250 and the number of wars from 95 to 252. Appendix 2 of (Lyall 2020a) reveals that these differences apply overwhelmingly in the 19th century, thus biasing the COW Inter-State data against the decline-of-war thesis by making the 19th century appear more peaceful than it really was.

A second advantage of Mars is that it begins coverage in 1800 rather than 1816 as COW does. COW introduces a further bias against the decline-of-war thesis by beginning (nominally) in 1816, after the massively violent Napoleonic War. In fact, CoW's first war is not until the Franco-Spanish War of 1823 while, between 1816 and 1823, Mars lists Bombardment of Algiers, Third Maratha War, Fifth Cape Frontier War, Ecuadorian War of Independence, Peruvian War of Independence, Greek War of Independence, Turko-Persian War, Brazilian War of Independence and Ashanti-British War in addition to COW's single war. Unfortunately, Mars only partially eliminates this starting-point bias since it still omits the earlier French Revolutionary and Seven Years Wars. Nevertheless, turning the clock back to 1800 is a step in the right direction.

Third, the Mars Project improves upon COW's erratic and poorly documented battle-death coding by revisiting all the numbers and explaining its decisions in a well-documented codebook.[13] For example, COW converts the 1980-1988 Iran-Iraq war into the 3rd biggest war in the whole dataset by overestimating its battle deaths by at least a factor of 2, with important implications for the decline-of-war debate. This case notwithstanding, anomalies in COW's death estimates pertain mostly to incompatibilities between the inter-state war numbers, on the one hand, and the intra-state and extra-systemic numbers on the other, with the latter often resembling excess deaths more than battle deaths. These incompatibilities do not affect the analysis of (Clauset 2018), (Braumoeller 2019) and (Cunen, Hjort, and Nygård 2020) since they use only the Inter-State data but they do affect (Fagan et al. 2020), (Spagat and van Weezel 2020) and (van Weezel 2020) which use the dataset described in (K. Gleditsch et al. 2004) which merges all COW datasets, uses their

[11] (Lybeck 2010) argues that a Eurocentric perspective gave rise to a myth of a peaceful 19th century. Europeans did curtail their fighting with one within Europe during this period but were highly active and aggressive outside of Europe.
[12] These wars, all international to various degrees despite their names, are included in the COW Intra-State dataset. However, (Clauset 2018), (Braumoeller 2019) and much of the IR field does not use this dataset so, as noted above, we focus on just the Inter-State data.
[13] (Lacina, Gleditsch, and Russett 2006) devote a section of their paper to exposing anomalies in COW's battle death coding and (Lacina 2009) covers this issue exhaustively for the post-1945 period.

battle-death numbers and then adds in some further wars to address some of the colonialism-driven omissions described above.

We present the critique of the decline-of-war thesis made in (Fazal 2014) and (Fazal and Poast 2021) here, rather than in section 1, since it is, primarily, a critique of COW. They argue that improvements in military medicine have, increasingly over time, converted (what previously would have been) deaths into injuries. Thus at least some of the observed post-World War 2 decline in battle deaths is illusory, in their view, because death statistics overlook large numbers of survivors who would have died in previous decades. Furthermore, COW's practice of coding only wars that cross a threshold of 1,000 battle deaths can lead to omission of whole wars that do not cross their contemporary threshold but might have if they had been conducted amidst the cruder military practices of bygone decades.[14] We agree with this critique on facts but differ on interpretation; the mobilization of science and organizational power to save lives does not, in our view, undermine the decline-of-war thesis but, rather, explains part of the observed decline in battle deaths.[15]

The analysis of (Fazal 2014) and (Fazal and Poast 2021) has the further virtue of highlighting the strong focus on battle deaths that derives from data limitations and pervades the decline-of-war debate and the conflict field more generally. Our understanding of war would be greatly enriched by consistent long-run data on war deaths of all varieties (civilians, diseases, excess deaths) as well as injuries not resulting in death. We do not, unfortunately, have such consistent data but we do have some pertinent information. Total deaths in the Taiping rebellion are thought to be in the 10's of millions (Platt 2012) as opposed to the roughly 100,000 KIA coded for Mars (and absence from COW Inter-State). (V. J. Cirillo 2008) finds that military personnel of the US died far more from infectious diseases than they did from "enemy actions" for all US wars until World War 2 reversed this pattern. Similarly, (Bailey 2013) finds dramatic long-term decreases in deaths from tropical and infectious diseases for British military personnel. These are just two countries, albeit among the ones most highly involved in wars and medical advances over the last two centuries, and their experience are likely to be similar to those of other European countries. These considerations suggest that the practical necessity of narrowing the scope of our analysis to battle deaths causes there to be a larger difference between total deaths and KIA counts before 1950 than after 1950 thereby introducing a strong bias against the decline-of-war thesis.

[14] The Mars data improves upon, while not eliminating, the inclusion threshold issue by setting a lower threshold of 500 KIA. Note that Mars also includes a handful of cases for which KIA is coded below 500 either because the high estimate of KIA is above 500 or because killings plus injuries are so high in these cases that the team judged that KIA must have been well above 500 even though were unable to specifically identify more than 500 KIA.

[15] Similarly, declines in maternal mortality rates in recent decades can be explained largely by improvements in technology and organization but this explanation does not negate the fact that there has been a decline.

3. The Korean War as a Turning Point in Two Centuries of Warfare

As noted above, (Fagan et al. 2020), (Cunen, Hjort, and Nygård 2020) and (Spagat and van Weezel 2020) all found evidence that 1950 was a change point in the history of war over the last two centuries.[16] But these were pure quantitative studies that did not assess the historical case for why 1950 marked a change in the distribution of battle deaths. This section considers the extent to which the historical record is consistent with the notion of 1950 as a change point, finding that, indeed, there was a pivot in world affairs occurring around the Korean War of 1950 – 1953. To be clear, peace did not break out after Korea and some phenomena, such as spiralling defence spending and the nuclear arms race, were decidedly aggressive. Thus, the change was not to a new era of peace but, rather, to managed competition that was more restrained than had been the case previously.

Before proceeding we should clarify that we do not attempt here, nor could we in a single section, a full explanation for the dynamics or war over the last two-plus centuries. Instead, we aim, much more modestly, to make a case for 1950 as a discontinuity point in these dynamics. Some of the factors already mentioned above, such as the progress of military medicine and the gradual discrediting of the idea of war as the solution to real problems, could play roles in a full explanation war dynamics but, we think, do not contribute to a discontinuity at 1950. Nevertheless, we will comment on a few post-1950 factors that reinforced decline, possibly extending to the present and future.

Robert Jervis, in a classic study (Jervis 1980) , identified the Korean War as the key turning point in the onset of the Cold War.

> "American policy during the height of the cold war was distinguished by the following features: (1) a high degree of conflict with the USSR; (2) a significant perceived threat of war; (3) high defense budgets; (4) large armies in Europe; (5) the perception of a united Sino-Soviet bloc; (6) the belief that limited wars were a major danger; and, following from the latter two beliefs, (7) anti-Communist commitments all over the globe. While the first and perhaps the second characteristics were present from 1946 to 1947, the other five came only after Korea." (Jervis 1980)

[16] Bear in mind that in the present, and earlier, studies wars are dated by their starting date so "post-1950" equate roughly to "after the Korean War" although this war did not end until 1953.

Forty years later, and with access to vastly more archival material than Jervis had when he wrote the above word, (Wells 2019) reached remarkably similar conclusions.[17]

(Gaddis 1974), (Warner 1980), (May 1984), (Trachtenberg 1988) and (Lafeber 1989) all make similar turning-point arguments, albeit with different nuances and emphases. (Gaddis 1974) and (May 1984) place Korea at the origin of a US commitment to contain communism all around the world with the US making little distinction between vital and peripheral interests. (Warner 1980) sees the Korean War as opening a major US/China rift and forging a (shaky) China/Soviet bond. (Trachtenberg 1988) portrays much of the US policy community shifting during and just after the Korean War from viewing nuclear war as winnable, and even desirable while the US held nuclear dominance, to widespread support for coexistence with the USSR and China. Post Korea there were vigorous struggles along the margins of each side's sphere of influence but all three powers broadly upheld the international status quo. (Lafeber 1989) argues that many of the big changes that coalesced during and just after the Korean war had earlier roots, but he still sees the war as transforming the nature, scope and scale of the NATO alliance.

(Foot 1985) demonstrates that that the Korean War came perilously close to going nuclear but, of course, did not and the war was ultimately dubbed, with good reason, "The Limited War" (Rees 1978). In fact, (Jervis 1980) argues that a well-formed concept of limited war was itself an outcome of the Korean War:

> "A war in Europe, it was assumed, would be unrestrained. Indeed, the whole concept of limited war which was to loom so salient after Korea was hardly present. As General Ridway(*sic*) explained, "The concept of 'limited warfare' never entered our councils" (1967: 11).…The decision makers had not rejected the idea of limited war; rather, they had not given it serious thought. Furthermore, consideration of it was inhibited by the same factors discussed above-to fight limited wars called for expensive capabilities which, in the prevailing political climate, the United States could not acquire. (Jervis 1980)

Fortunately, the concept of limited war took hold before Armageddon was ignited yet the toll was still horrific on all sides.[18] Thus, point (6) of (Jervis 1980) above applies; limited war had become an option but it was, potentially, a very costly one.

The Korean War also provided a double test of rollback policies. The broad contour of the war was that, first, North Korea (with Soviet and Chinese support) tried to take

[17] See Jervis' review of Wells' book (Jervis 2021). (Wells 2019) adds his contention that, contrary to his earlier view, the US was correct to fear the worst about the Soviet military build-up.

[18] (Lyall 2020) codes a range of 543,936 to 718,099 battle deaths for the Korean War and, of course, battle deaths are only part of the full cost of the war.

over the south. Second, the UN (but mainly the US and South Korea) repelled this invasion and then tried unsuccessfully to take over the north. That is, two rollback adventures led to catastrophes and the two sides eventually settled on mutual containment.[19] Thus, the Korean War provided a cautionary tale: bold military moves to upset the global status quo are very risky.

In short, the quantitative literature identifying a decline of war beginning in 1950 is consistent with the historical record that finds the Korean War to be a transitionary event toward a tense Cold War stand-off that was, nevertheless, more restrained and less violent than the preceding period in global politics. To be sure, global peace did not break out after the Korean War as (Chamberlin 2018) documents all too well. In fact, the Korean war stimulated an arms race and aggressive US/Soviet confrontations all around the globe. Yet it also alerted US and Soviet leaders to the necessity of managing their rivalry while also showing in microcosm how they might do so.

Finally, we single out three further factors that have worked to contain war violence in recent decades, although they do not contribute to a discontinuity at 1950. First is UN peacekeeping, convincingly demonstrated by (Fortna 2008) to work and strongly emphasized by (Goldstein 2012) in his account of the decline of war. Second is a shift toward more "humane war" (Moyn 2022) that began during the Vietnam War and that has reduced war violence, albeit without ending war. Third is the end of the Cold War which reduced international tensions

4. Problems with the New Decline-of-War Thesis and Predictions of Doom

Before we proceed to our analysis of the Mars data we engage in this section with the recent decline-of-war technique that has received considerable attention. Section 2 (above) suggests that all analysis based on COW Inter-State should be reevaluated. Moreover, we argue below that the critique has further flaws that have not yet been widely understood.

The case of (Clauset 2018) and (Braumoeller 2019) against the decline-of-war thesis is, to a large extent, based on their failure to reject a hypothesis that a single power law fits the distribution of Inter-State war sizes for both 1816-2007 and 1946-2007.[20] The first limitation of the unchanging power-law argument is that the evidence for a power law in COW war sizes is weak; many other distributions are just as plausible as a power law. For example, (Clauset 2018) fits a power law with a survival function of $109.62 * x^{-0.53}$ that applies above a minimum war size of 7,061. This is a reasonable choice and we nearly replicated these results using the poweRlaw package (Gillespie 2020), obtaining a slightly different coefficient of -0.51 that

[19] See any narrative history of the Korean War such as (Hastings 2012).

[20] Note that (Braumoeller 2019) emphasizes a war-size measure he calls "intensity", i.e, battle deaths divided by the country's population whereas (Clauset 2018) works with the raw battle death numbers. We will work with just raw battle deaths but the ideas here are applicable to both measures.

applies above a minimum war size of $6{,}525$. We estimated a p value of 0.63 on the Kolmogorov-Smirnov test of the hypothesis that the data was generated by the estimated power law, broadly consistent with the findings of (Clauset 2018). So this power law is not rejected by the data. However, other fat-tailed distributions can easily be mistaken for power laws (Stumpf and Porter 2012) so (Clauset, Shalizi, and Newman 2009) recommends testing power-law estimates against alternative fat-tailed distributions such as lognormals and exponentials. We follow this advice and find that these tests do not give pride of place to the power law. Indeed, the test of (Vuong 1989), as implemented in the poweRlaw package, finds the power law and lognormal to be equally plausible (Z value of -0.33) although the power law does come out weakly preferred to the exponential (Z value of 1.6).

These distributions are but three out of many types of fat-tailed distributions so we used the GAMLSS package of (Stasinopoulos et al. 2017) to explore a wide range of possibilities.[21] A generalized gamma distribution was the best fit to the Inter-state COW data with an AIC statistic of the 2140 while the power law and lognormal ranked 11th and 13th respectively, with AIC scores of 2174 and 2188, respectively. Model selection based on minimizing AIC is not good practice but these comparisons do show that there is no reason to favor a power law over a number of other distributions. Figure 1 visually confirms this observation; the power law does not stand out as, somehow, the “correct” fit. Of course, the argument for an unchanging power law, pre and post-World War 2, is undermined to the extent that COW war sizes are not even governed by a power law in the first place.

The findings in the previous paragraph led us to discover that evidence singling out a power law in war sizes is also weak in the Mars data. The Vuong test renders the power law and lognormal to be equally plausible for both the low and high estimates of KIA counts, with Z values of -0.03 and -0.52 respectively. The power law is weakly preferred to the exponential for the high estimates of KIA (Z value of 1.51) but not particularly favored for the low estimates (Z = 1.15). The GAMLSS package does place the best power law 6th and 5th according to the AIC statistic, respectively, for the low and high KIA estimates among all the distributions considered. Again, these exact ranking mean little but the analysis does show that there are plenty of plausible alternatives to power laws..

Figure 1

A second limitation of the unchanging power law argument is that it assumes that this one curve governs war sizes all the way up through arbitrarily large values. The standard log-log presentation of power law fits (figure 1) obscures the sheer boldness of this extrapolation. Figure 2 displays the same three curves in natural units together with the post-1945 COW war sizes. All three curves look like plausible fits to the post-1945 data points. But their extensions into the massive space beyond the data beyond the data look almost arbitrary, not least because they differ hugely from each other. Moreover, figure 2 shows merely three possible ways to describe a

[21] Note that the poweRlaw package fits a distribution to just the tail of the data whereas GAMLSS seeks a distribution that best describes the entirety of the data.

relationship about which we have no actual post-1945 data. A wide range of both slower and faster approaches toward 0 are roughly as plausible as the ones displayed in the graph, at least in the absence of some further analysis beyond simple curve fitting. In short, it could be useful for some purposes to model the data as fitting a single power law within some range, but it is quite an unjustified leap to assume that this curve has predictive value over an order of magnitude beyond the range of the post-1945 data.

Figure 2

Finally, consider the following doomsday warning which provides a convenient opportunity to summarize much of the present paper so far:

> "When I sat down to write this conclusion, I briefly considered typing, 'We're all going to die,' and leaving it at that. I chose to write more, not because that conclusion is too alarmist, but because it's not specific enough….
>
> …If the parameters that govern the mechanism by which wars escalate hasn't changed—and there's no evidence to indicate that they have—it's not at all unlikely that another war that would surpass the two World Wars in lethality will happen in your lifetime. And if it is bigger than the two World Wars, it could easily be a *lot* bigger.[22]" (Braumoeller 2019)

This warning may be offered more as a spur to action than as a serious prediction but it does not work as a prediction because it relies on the unreliable and incomplete COW Inter-State war data and assumes that war sizes are truly governed by a power law that continues to apply up to arbitrarily large sizes, including those more than an order of magnitude beyond all post-1945 data. Of course, all prediction about the future must extrapolate beyond known data and there is no bright line that separates reasonable from unreasonable extrapolation. We suggest, nevertheless, that the above doomsday prediction has crossed the line.

5. Descriptive Statistics for the Mars Database

The following analysis uses four different Mars-based measures of war sizes: high and low estimates of KIA counts in both raw form and per 100,000 of world population. The reason for the population adjustment is to roughly approximate the probability that a random person alive at any point in time will be killed in action. Population adjusted war sizes are interesting for the same reason population adjusted homicide rates are interesting. For example, India's homicide rate in 2018

[22] Note that the failure of (Braumoeller 2019) to reject a hypothesis of no change in a power law coefficient does not imply that there is no evidence of a change war escalation mechanisms and, indeed, (Cunen, Hjort, and Nygård 2020), (Fagan et al. 2020) and (Spagat and van Weezel 2020) all found such evidence.

was less than 1/16th the El Salvadoran rate but India had more than 12 times the total homicides of El Salvador (Murder Rate by Country 2022 n.d.). These facts are both interesting useful in different contexts. Similarly, we think that both absolute and population-adjusted war sizes are relevant to the decline of war debate.

Table 1 gives both high and low per annum estimates of total KIA and KIA per 100,000 of world population, based on the Mars data, for the 19th century, 1900-1950 and 1951-2011.[23] Unsurprisingly, 1900-1950 has far more KIA per annum than the other periods. More interestingly, per annum post-1950 KIA counts exceed 2/3 of their 19th century counterparts and, once we adjust for world population, both post-1950 rate more than double the 19th century ones. Moreover, the 19th century war arrival rate nearly doubles the post-1950 rate and, surprisingly, greatly exceeds the arrival rate for the exceptionally violent first half of the 20th century.

The COW Inter-State data, summarized in Table 2, tells a very different story. Annual 19th century battle deaths (the COW equivalent of KIA) fall just below 1/3 of their post-1950 counterpart and the former period remains just below the latter one even when we adjust for world population. Moreover, COW places the 19th century war arrival rate at only half that of the other two periods. These comparisons succinctly illuminate how the COW data has perpetuated a "myth of the hundred years peace" already challenged in detail by (Lybeck 2010).[24] Table 3 shows the 20 wars with the highest KIA counts that are excluded by COW Inter-State but included in Mars. Half are in the 19th century and only 3 are after 1950. Most exclusions are attributable either to non-recognition of belligerents by the colonial powers or to COW's post-1815 start, although we have no explanation for the exclusion of the takeover of South Vietnam by North Vietnam.

Table 1

Table 2

Table 3

Table 4 provides the five-number summaries for distributions suggested by John Tukey (Hoaglin, Mosteller, and Tukey 1983), The middle of the distributions for raw KIA counts are actually higher after 1950 than they before 1950 although the reverse is true for population-adjusted counts. This is interesting information but note that it takes no account at the rates at which wars of various sizes arrived.

Table 4

[23] Recall that we date wars by their start year so, for example, all KIA in the Korean war are placed in 1950.
[24] The title of chapter 1 of (Polanyi 2002) is "The Hundred Years Peace."

Figure 3 provides three different versions of the time series of the low estimates for Killed in Action according to the Mars data.[25] Panel a shows little more than that the two World Wars dwarf everything else. Panels b and c fix the World Wars problem by, respectively, logging the Y axis and showing a 30-year moving average. Panel c is, perhaps, the most informative although it is roughly what one might expect after seeing Table 1.

Figure 3

Figure 4 attempts to uncover possible turning points in the last two centuries of war by plotting a series of forward averages for both the low and high estimates of KIA. Each point on one of the curves gives the mean number of KIA per year from that year forward to 2011 (when the data stops). We also orient readers by labelling some large wars and marking means for several time periods. The picture is dominated by the extreme violence for the first half of the twentieth century followed by a precipitous drop as this period closes with the Korean War. Subsequently, forward means decrease almost monotonically.

Figure 4

In short, the summary statistics of this section show the COW data underestimating 19th century relative to post-1950 war violence. They also are consistent with the idea of a post-1950 decline of war, as shown in table 2.

6. Testing Many Hypotheses of no Change after 1950

Suppose that war arrivals between 1800 and 1950 follow a Poisson process with rate parameter equal to their empirical arrival rate during this time period which is roughly 1.34 per year. If the underlying war arrivals process did not change in 1950 then this same rate of 1.34 should apply to 1951-2011, a period when Mars records 49 wars. We can calculate that the probability of 49 or fewer wars during 61 years with a war arrival rate of 1.34 is less than 0.0001, a p value that constitutes extremely strong evidence of a post-1950 slowdown in war arrivals. Next, we restrict attention to wars arrivals with low estimates of KIA counts above the median for 1800-2011 which is 4,178. The pre-1950 arrival rate is roughly 0.65 and there are 28 post-1950 wars with KIA counts above 4,178. Now the hypothesis of no post-1950

[25] The same graphs for the high estimates are visually indistinguishable from figure 3.

changes leads to a p value (probability of 29 or fewer wars) somewhat above 0.03: good evidence of a post-1950 slowdown.

We now build on the approach of the previous paragraph to conduct many hypothesis tests. These use both low and high KIA estimates, both raw and population-adjusted measures and every possible floor for KIA counts, i.e., not just 0 and the median as were used above. The main idea throughout is that if there is no change in 1950 then we should be able to split our sample into pre-1950 and post-1950 components that behave the same aside from random variation. More formally, we always test the hypothesis that war arrivals after 1950 follow a Poisson process with arrival rate equal to the pre-1950 arrival rate against the alternative hypothesis that the post-1950 war arrival rate is slower than the pre-1950 empirical rate. While digesting the following algorithm which implements the just-described ideas the reader should bear in mind that there are 151 years between 1800 and 1950 and 61 years between 1951 and 2011.

1. Fix a minimum war size, S.

2. Define N(S) to be the number of wars between 1800 and 1950 that are at least as large as S.

3. Set the central prediction for the number of wars between 1951 and 2011 of size S or larger equal to N(S)*61/151.

4. Set 0.025 and 0.1 lower prediction limits for wars between 1951 and 2011 equal to percentiles 2.5 and 10, respectively, of the Poisson distribution with arrival rate parameter equal to N(S)*61/151.[26]

5. Repeat steps 1-4 for all S.

The general idea is that the empirical arrival rate of pre-1950 wars with more than S KIA is N(S)/151 and if we set this equal to the post 1950 Poisson arrival then N(S)*61/151 gives the predicted number of post-1950 arrivals with KIA great than S. Percentiles 2.5 and 10 are derived from the same Poisson process.

Figure 5

Figure 5 displays the results of these procedures, plotted on logarithmic X axes, with the top panel using the low estimates of KIA while the bottom panel uses the high

[26] We run discrete, one-sample, Kolmogorov-Smirnov (KS) tests of the hypothesis that war arrival rates follow a Poisson process for the periods 1800 – 2011, 1800 – 1950 and 1951 to 2011 using the iZID package in R, obtaining p values, respectively, of 0.35, 0.9 and 0.27. This suggests that it is reasonable to model the war arrival process as following a Poisson distribution.

estimates. Note first that when we use most of the data, e.g., setting the minimum KIA count at around 3,000 then we resoundingly reject the hypothesis of no change in war arrival rates of all sizes for 1951 – 2011 compared to 1800 - 1950, against an alternative hypothesis of slowdown. Moreover, the central predictions for numbers of post-1950 wars are always (almost always) lower than the actual number of post-1950 wars in every size range for the low estimates (high estimates) of KIA. The bottom 2.5% of the prediction intervals exceed the actual number of wars for every size range up to around 4,000 and above (6,000 and above) for the low (high) estimates of KIA. The corresponding cut-offs for the bottom 10% of predictions are around 8,000 for both the low and high KIA estimates. So at least until S rises above its median level we can rather confidently reject all no-change hypotheses in favour of a slowdown of war arrival rates.

The above hypothesis tests can easily fail to reject (at a standard significance level) a no-change hypothesis for war arrivals with KIA counts above some value, S, even when there truly is a post-1950 slowdown. Intuitively, these false negatives tend to occur when S is relatively large, implying that arrival rates are slow and, hence, sample sizes are small. The following power analysis formalizes this intuition; unless there is a very large slowdown, the present methods have only a weak ability to detect real post-1950 declines in war arrival rates once the bottom of the KIA count range is much above its median value. These simulations assume a pre-1950 Poisson arrival process followed by a slower post-1950 Poisson arrival process and calculate the probability that we will obtain a statistically significant rejection of the no-change hypothesis under these circumstances. We repeat these calculations for many pre-1950 arrival rates and slowdown factors. Following this logic, the points on the curves in figure 6 are calculated as follows:

1. Set a Poisson arrival rate, A, meant to represent arrivals of wars above some size, S, between 1800 and 1950.

2. Set a slowdown factor, F, equal to 0.9. 0.8, 0.7, 0.6 or 0.5.

3. Calculate the probability that the number of arrivals generated over 61 years by a Poisson process with arrival rate F*A falls below percentile 2.5 of a 61-year Poisson process with arrival rate A.

4. Repeat and graph these calculations for many arrival rates and each of the slowdown factors.

Figure 6 shows the results of these power calculations. Note that these are not based on the Mars data however, for orientation, we also show the arrival rate for wars with low estimates of their KIA counts above the median in the Mars. Around this median arrival rate there is less than a 50% chance of detecting, with statistical significance, a 30% post-1950 slowdown (slowdown factor of 0.7). 40 or 50% slowdown factors are likely to be detected even for war arrival rates well below the median rate observed in the Mars data. But we are unlikely to detect 10 or 20 percent slowdowns even if we begin with an arrival rate of 1.5 wars per year, which is the rate recorded for wars of all sizes in the 19^{th} century and never reached again. Thus, our failure, displayed in figure 5, to reject no-change hypotheses for KIA ranges bounded from below by values distinctly above the median KIA count constitutes, at best, weak evidence for no change within these relatively high ranges. As is suggested by the point estimates, there might actually have been substantial slowdowns within these ranges,

Figure 6

Figure 7 is constructed in the same way that figure 5 is except that now we use KIA per 100,000 of world population rather than raw KIA numbers. Now the evidence for a post-1950 decline of war becomes very strong. Figure 7 shows that the bottom 2.5% of the prediction range exceeds the actual number wars for every size range up to around 2.7 per 100,000 and above (3.9 and above) for the low (high) estimates of KIA. The corresponding cut-offs for the bottom 10% of the prediction ranges are around 10.1 and 8.8 for the low and high estimates respectively. The current world population is roughly 7.9 billion people, so these numbers translate into contemporary absolute war sizes between approximately 200,000 and 800,000 KIA. In short, once we adjust for world population, we can be very confident in a slowdown of war arrival rates even for ranges that begin at very large KIA counts.

Figure 7

Table 5 gives the results of a forward-looking exercise that calculates the numbers of wars that would have to occur during the 20 years since the last year covered in the Mars dataset to cause rejection of various no-change hypotheses at the 0.05 level. For example, 4 wars with low estimates of KIA counts above the 3^{rd} Quartile for the whole (present) dataset would tip the p value on the no-change hypothesis above 0.05 leading to a failure to reject at the 0.05 significance level. For orientation, there were 5 such wars between 1992 and 2011 although none started during the last 13 years of this period. We judge very unlikely that any of the numbers in Table 5 will be reached other than the ranged above the 3^{rd} quartile for the low and high estimates of KIA and even these could go either way.

A weakness of the whole approach of this section is, however, that it does not allow us to attach probabilities to the decline of war thesis. We turn, therefore, to a Bayesian approach in the next section.

7. Bayesian Analysis Suggests that War went into Decline after 1950

The basic ideas of this section are as follows. For any KIA measure, S, we set a Bayesian prior probability distribution for the arrival rate of wars with KIA measures above S. This is an informed prior because we set its mean equal to the pre-1950 arrival rate of wars with KIA measures above S. Thus, through our choice of mean we embed a no-change assumption directly into the prior thereby stacking the deck against the decline-of-war thesis. We then combine the post-1950 war arrival data with the prior to convert it into a posterior distribution over the post-1950 arrival rate of wars with KIA measures above S. The posterior is our estimate of the post-1950 arrival rate in this range.

Figure 8 illustrates the Bayesian approach of this section in an example with the minimum KIA count S set equal to 5,000, for both high and low estimates. The vertical dotted line in each panel is the empirical arrival rate between 1800 and 1950 for wars with KIA counts above 5,000. The solid curves are Bayesian prior distributions over the arrival rate of wars in this size range which are gamma distributions with means equal to the corresponding 1800 – 1950 arrival rates.[27] We offer high and low variance versions of these priors in neighbouring panel. The dashed curves are the posterior distributions over the post-1950 arrival rates of wars with KIA counts above 5,000. The gamma distribution is conjugate to itself, so these posterior distributions are also gamma distributions but with much smaller means and variances than the priors. Our initial assumptions plus the data imply that there is a 50% chance that the true post-1950 arrival rate for wars above the size of 5,000 KIA lies within the shaded area in each panel.

Figure 8

Figure 8 captures the essence of our approach here but we cannot create a picture that shows prior-posterior transformations for a large number of KIA ranges, so we provide two alternatives. First, in the appendix we provide R code that leads to a function enabling anybody to produce pictures like figure 8 at will for any measure, including KIA per 100,000, and any range. Second, figure 9 shows estimated probabilities that post-1950 arrival rates are less than pre-1950 arrival rates for many size ranges. Each such probability is the mass of the posterior probability distribution

[27] The X axes in the pictures are truncated at 1 so the means of the priors really do equal the pre-1950 arrival rates even though the pictures seem to suggest otherwise.

that is below the pre-1950 arrival rate for that KIA range. For example, the point above 10,000 in the upper left panel shows an estimated probability above 0.75 that the post-1950 arrival rate for wars with KIA counts above 10,000 is lower than the pre-1950 arrival rate for wars in this same range. This curve does show that slowdown and no change have roughly equal probability when the ranges start at around 80,000 KIA. But as the bottom of the range decreases below 10,000 the slowdown probabilities creep above 0.9. Eventually, when we use almost all the data, the slowdown probabilities are near 1.[28]

Figure 9

Figure 10 is constructed exactly like figure 9 but for KIA counts adjusted for world population. Now the probability of post-1950 slowdown never dips below 0.75 and is mostly near 1.

Figure 10

8. Conclusion

In this paper we build on several evidence streams. First is the qualitative historical record, summarized in section 3, that pinpoints the Korean War as a key turning point in the Cold War. Second is what might be called the "Long Peace School", beginning with (Gaddis 1986) and surveyed in section 1, that identifies declining trends in a variety of post-World War II violence indicators and proposes explanations based on, *inter alia*, political, institutional and cultural factors. Third is the critique of this Long Peace School, also discussed in section 1, that uses the fat-tail property of the distribution of war sizes to argue that at least some of the declining trends identified by the School are consistent with an unchanged underlying war-generation mechanism. This critique is a particularly important motivation for the present paper so we devote section 4 to a rebuttal. Last are several recent quantitative papers that found evidence for a post-1950 decline of war using a variety of methods. All these papers are, however, based on the COW data which is seriously flawed as discussed in section 2.

The new Mars data provides a high-quality alternative to COW Inter-State and the main contribution of our paper is to introduce it into the decline of war debate and

[28] The top and bottom panels look identical to each other but there is no mistake; we have verified that the underlying numbers are slightly different. We learn that the variance of the prior has no practical effect on the posteriors. The same is true of figure 10.

use it to analyse the relationship between arrival rate and war size within the data. The exploratory analysis of the Mars data in section 5 in section five points towards of post-1950 slowdown in war arrival rates while exposing the strong tendency of CoW Inter-State to underplay 19th century war violence. The more formal analysis of the next two sections, presented in both NHST (section 6) and Bayesian (section 7) frameworks, strongly support the post-1950-slowdown idea. When we use all the data, i.e., when we consider the arrival rates of wars of all sizes, the evidence for a post-1950 slowdown is overwhelming. Even when we restrict attention to wars with KIA counts above the first quartile (above the median) for all wars between 1800 and 2011 the evidence for a post 1950 slowdown remains very strong (strong). We do not find good evidence of a slow in war arrival rates with KIA counts above the 3rd quartile, but our power analysis reveals that little ability to detect such changes even if they exist.[29] A robustness exercise shows that new data through 2031 is unlikely to reverse any of the above results, except possibly for those covering the range above the 3rd quantile.

When we measure war sizes in population-adjusted, rather than absolute, terms then the evidence for post-1950 slowdown remains strong even for ranges that are bounded from below by very low values of KIA per 100,000 or world population. If we convert these values into raw KIA counts using contemporary populations then these lower bounds, above which there is strong evidence of slowdown, can be well into the 100's of thousands. Of course, one can always consider a range that is bounded from below by a very large number and find the evidence for slowdown within this range to be weak but there is no real positive evidence in favour of a no-change hypothesis for these very high ranges.

The Bayesian analysis allows us to derive probability distributions over the post-1950 arrival rates of wars in all size ranges. For raw KIA counts, the means of these distributions for are, aside from a handful of ranges, below their pre-1950 counterparts and the probabilities of decline approach 1 as the bottoms of the ranges decrease towards 0. When we use population-adjusted war KIA counts then decline probabilities never dip below 0.75 and are generally much higher. We embed a no-change hypothesis into the prior probability distributions underlying these calculations thereby stacking the deck against a finding of slowdown. Based on our past research our honest priors would favour slowdown and these would lead to conclusions still more in favour of slowdown than those reported just above in this paragraph. A distinct advantage of the Bayesian approach is that anyone can experiment with their own priors, size ranges and measures and discover how these translate into posteriors. We enable such experimentation through a simple facility provided in the appendix.

[29] Remember that higher lower bounds for KIA counts imply smaller sample sizes which compromise our ability to detect slowdowns that might truly have occurred.

An important further finding of this paper is that there is no special connection between power laws and the distribution of war sizes; many other distributions are at least as plausible as power laws. For some analyses it could be useful to proceed as if war sizes obey a power law since the war size distribution does have a fat tail and power laws are relatively simple to work with. However, when one extrapolates far beyond existing data, as has been done in the decline-of-war debate, then the power law assumption is not merely a convenient stylization of the data but, rather, the main driver of all predictions. Other plausible assumptions for extrapolating the data lead to dramatically different predictions.

The above analysis focuses on comparing 1800 – 1950 with 1951 to 2011. The findings are of intrinsic historical interest as they illuminate the dynamics of warfare. They have potential policy relevance as well by suggesting that at least some of the policy measures undertaken in recent decades by the international community to reduce the scourge of war have helped and should be continued and extended. Regarding the future, we must bear in mind that the slowdown we have identified could be, or might already have been, reversed due to some big change in the world such as global warming or the war in Ukraine. Nevertheless, the recent past is usually a good starting point for predicting the future and we would cautiously venture the prediction that the warfare experience of the next few decades will resemble1951 – 2011 more than 1800 – 1950.

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Table 1 - Killed in Action and Number of Wars Per Annum for Three Time Periods

periods	Low[1]	High[2]	Low per 100,000[3]	High per 100,000[4]	Number of Wars
1800-1899	22,667	34,812	1.8741151	2.783990	1.5
1900-1950	645,281	942,821	29.8500276	43.348773	1.0
1951-2011	32,372	50,403	0.8531089	1.277471	0.8

[1] Using the low estimates of killed in action

[2] Using the high estimates of killed in action

[3] Using the low estimates of killed in action per 100,000 of world population

[4] Using the high estimates of killed in action per 100,000 of world population

Data: Project Mars

Table 2 - Battle Deaths and Number of Wars Per Annum for Various Time Periods

Periods	Battle Deaths	Battle Deaths per 100,000	Number of Wars
1800-1899	14,000	1.0	0.3
1900-1950	550,112	26.0	0.6
1951-2011	43,035	1.1	0.6

Data: Correlates of War

The Twenty Biggest Wars Excluded from CoW

Ordered by the low estimates of Killed in Action

War Name	kialow	kiahigh	Start Year	End Year
Chinese Civil War	1,200,000	2,071,610	1946	1949
Napoleonic Wars	570,328	598,225	1800	1815
Russian Civil War	379,483	858,742	1918	1921
Spanish Civil War	203,839	288,150	1936	1939
Warlord Era: Anhui-Zhili War	193,400	280,300	1920	1930
American Civil War	166,040	229,000	1861	1865
Tigrean and Eritrean War	126,000	315,000	1982	1991
Thousand Days' War	100,000	100,000	1899	1902
Taiping Rebellion	95,000	111,000	1851	1864
North Yemen Civil War	84,000	100,000	1962	1969
Battle of Shanghai	64,770	74,870	1931	1932
Rif War	54,370	70,000	1921	1926
First Mahdi War	46,349	56,461	1881	1885
Durrani Empire-Sikh War	40,400	56,900	1813	1823
Ethiopian-Mahdi War	40,000	75,000	1885	1889
November Uprising	37,900	37,900	1831	1831
Second Maratha War	31,868	39,696	1803	1805
Vientiane-Siam War	31,000	31,000	1827	1827
Satsuma Rebellion	26,300	26,300	1877	1877
North Vietnam-South Vietnam	26,100	43,500	1974	1975

Data: Project Mars and CoW

Table 4 - Tukey's Five Numbers

Various KIA Measures and Time Periods

	Minimum	Quartile 1	Median	Quartile 3	Maximum
Low Estimate of Killed in Action					
1800-2011	30	1,539	4,178	13,123	21,058,659
1800-1950	30	1,742	4,000	12,138	21,058,659
1951-2011	206	1,200	5,750	15,200	228,220
High Estimate of Killed in Action					
1800-2011	30	2,734	7,298	20,182	30,859,974
1800-1950	30	2,900	6,475	19,801	30,859,974
1951-2011	244	1,700	10,386	30,442	578,000
Low Estimate of Killed in Action per 100,000					
1800-2011	0.002	0.096	0.259	0.733	921.281
1800-1950	0.002	0.116	0.289	0.879	921.281
1951-2011	0.003	0.025	0.134	0.307	5.116
High Estimate of Killed in Action per 100,000					
1800-2011	0.002	0.165	0.445	1.321	1,350.072
1800-1950	0.002	0.194	0.494	1.435	1,350.072
1951-2011	0.004	0.038	0.205	0.641	12.958

Data: Project Mars

Table 5 - Numbers of Wars between 2012 and 2031 Required for Non-Rejection of No-Change Hypotheses

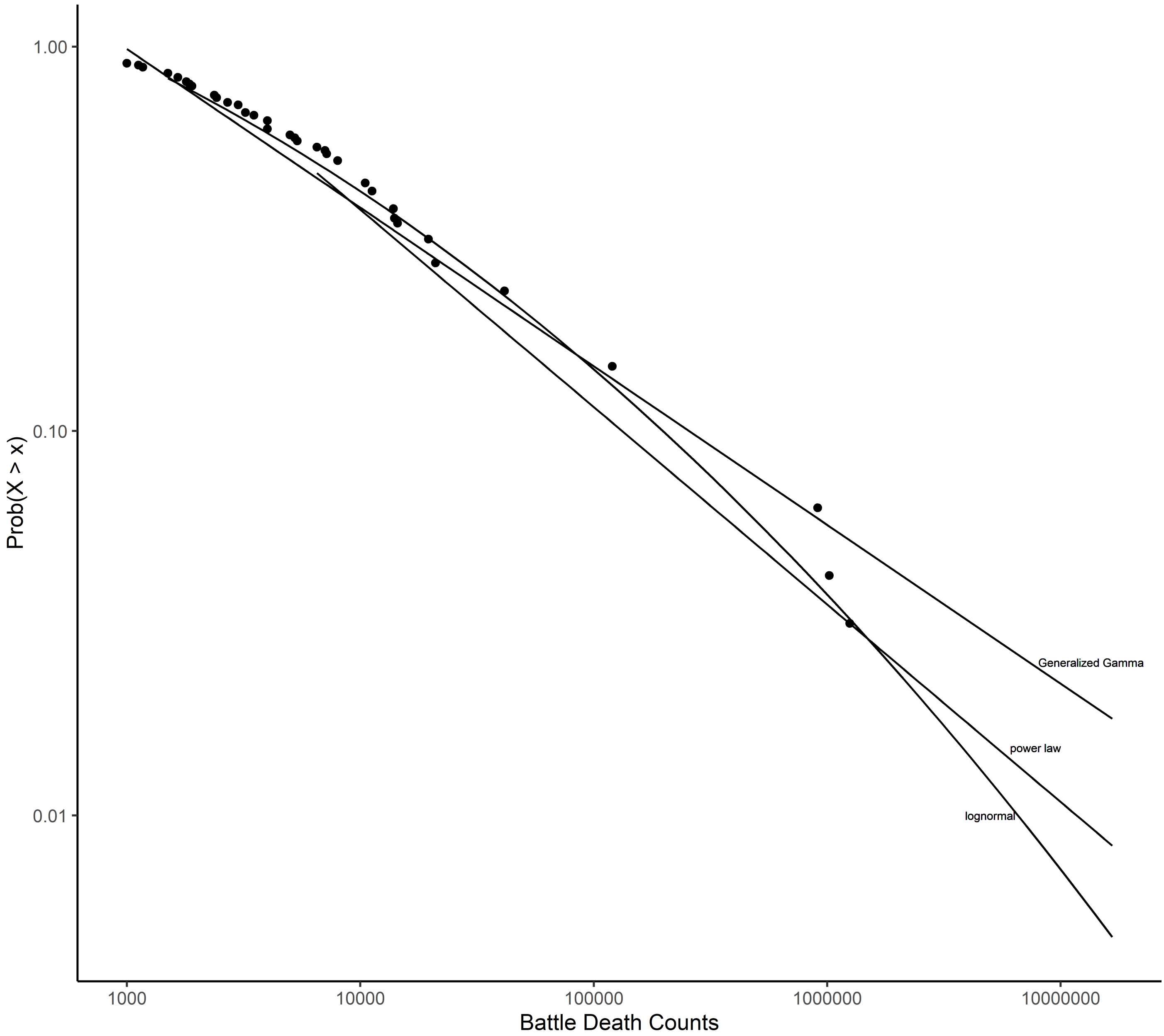
Various KIA Measures and Time Periods

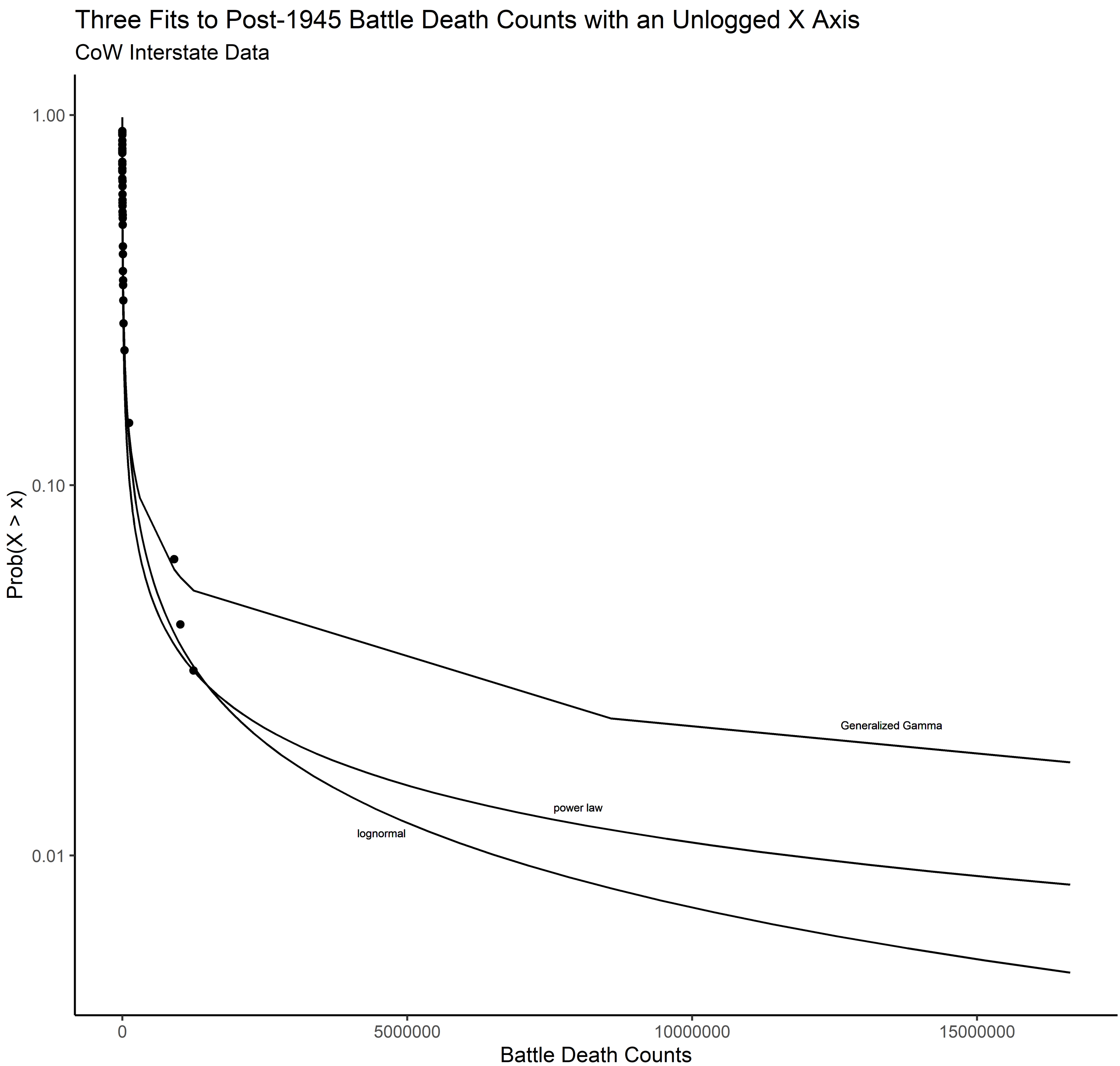
Measures	Above Quartile 1	Above the Median	Above Quartile 3
Low Estimates of KIA	34	13	4
High Estimates of KIA	34	11	4
Low Estimates of KIA per 100,000	43	31	14
High Estimates of KIA per 100,000	43	31	11

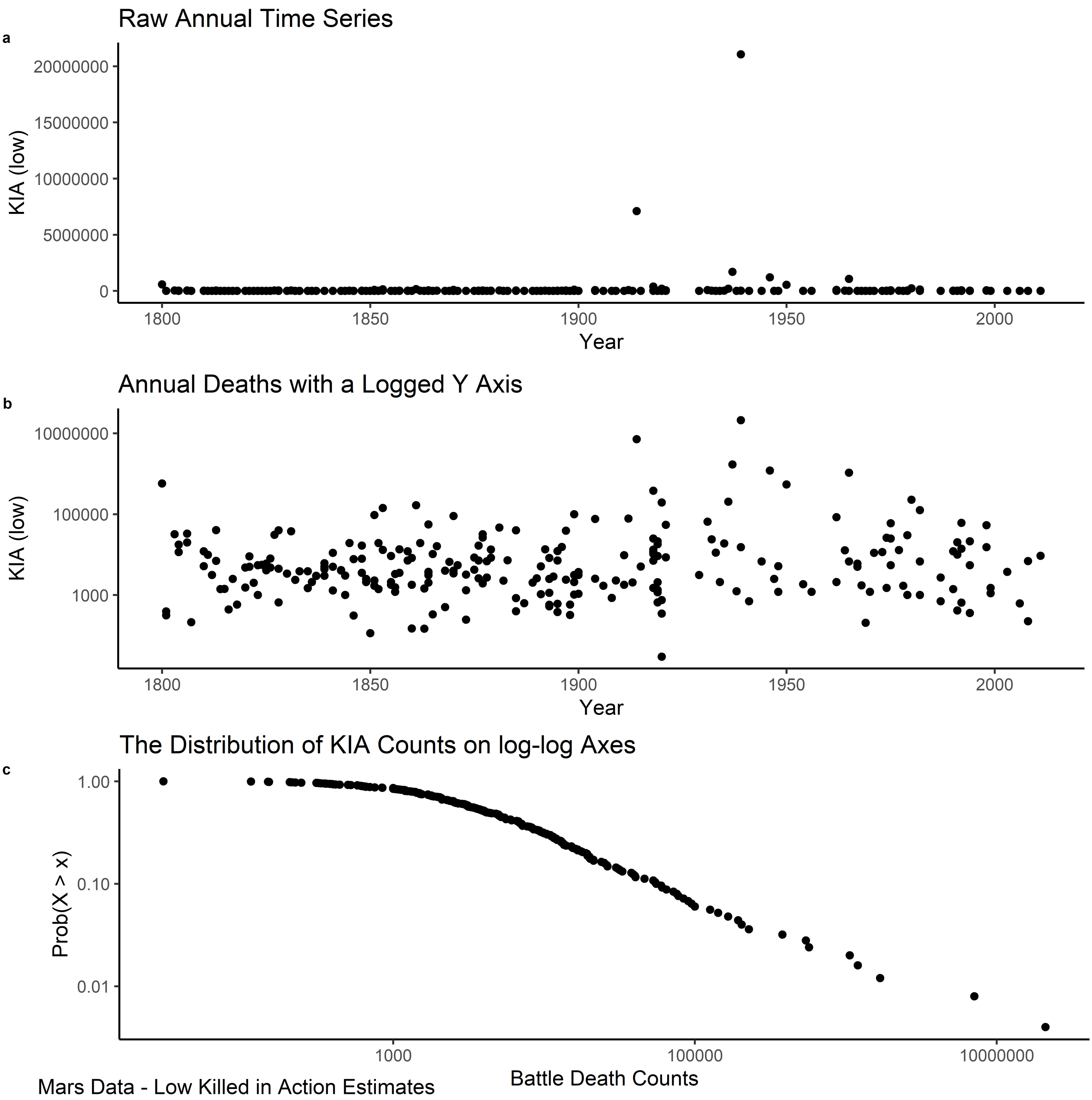
Each table entry gives the number of wars required to push the p value on the corresponding no-change hypothesis above 0.05. For example, if there are 34 wars between 2012 and 2031 with low estimates of KIA counts above the 1st quartile of KIA counts for 1800-2011 then we would (just) fail to reject the no-change hypothesis for wars in this size range. Data: Project Mars

Power Law, Lognormal and Generalized Gamma Fits Battle Death Counts

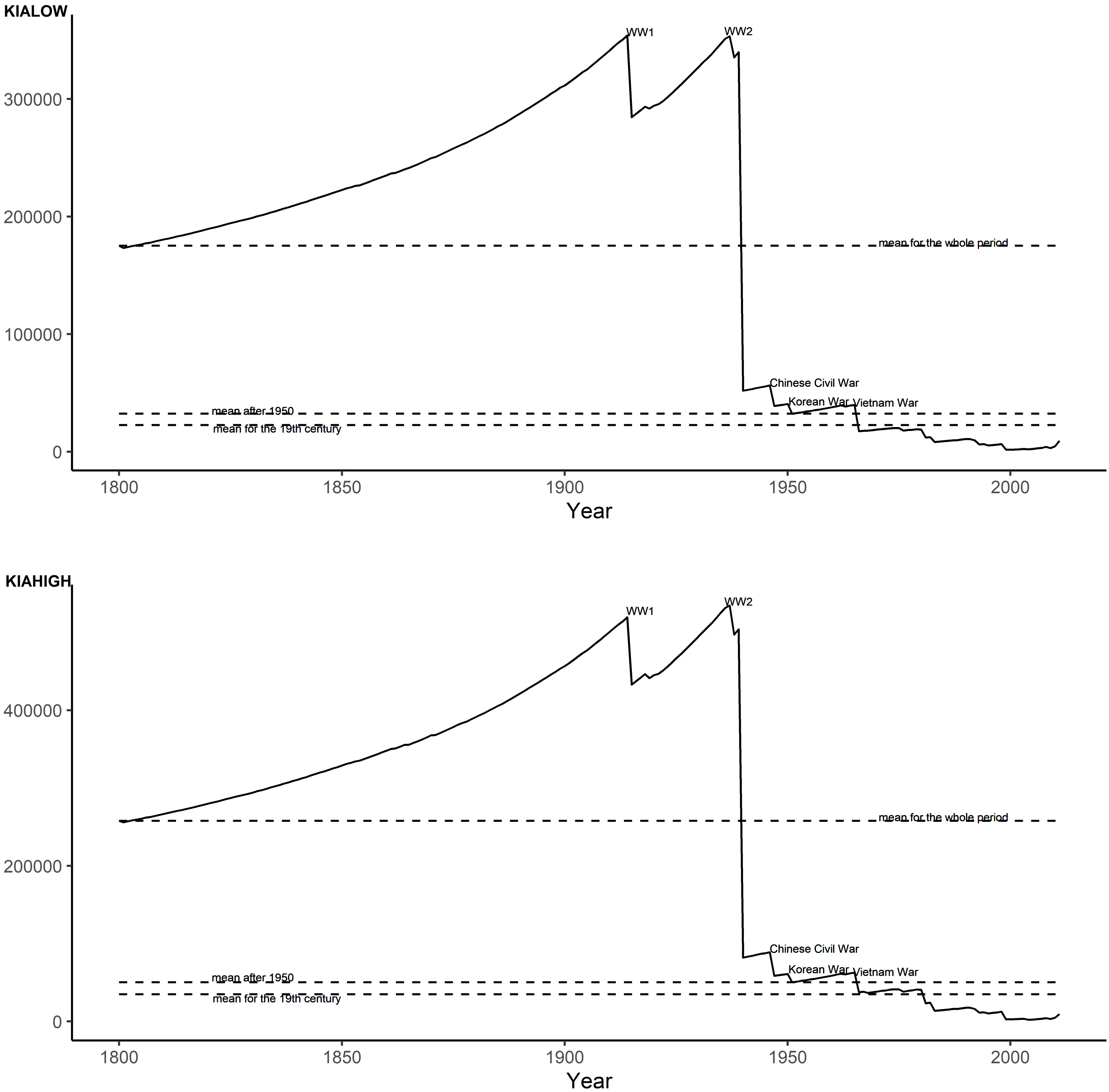
CoW Interstate Data - just the post World War 2 data points shown

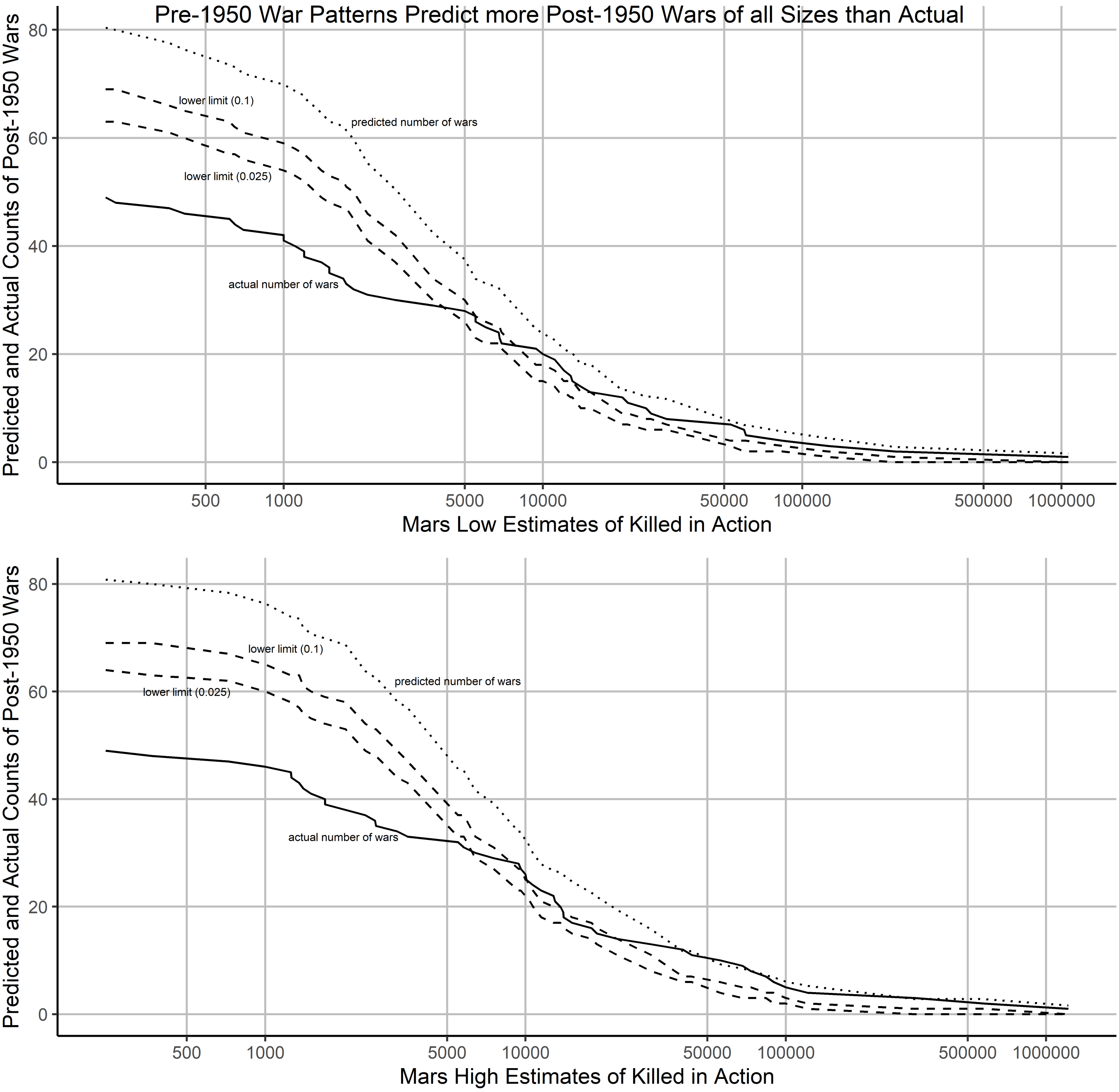


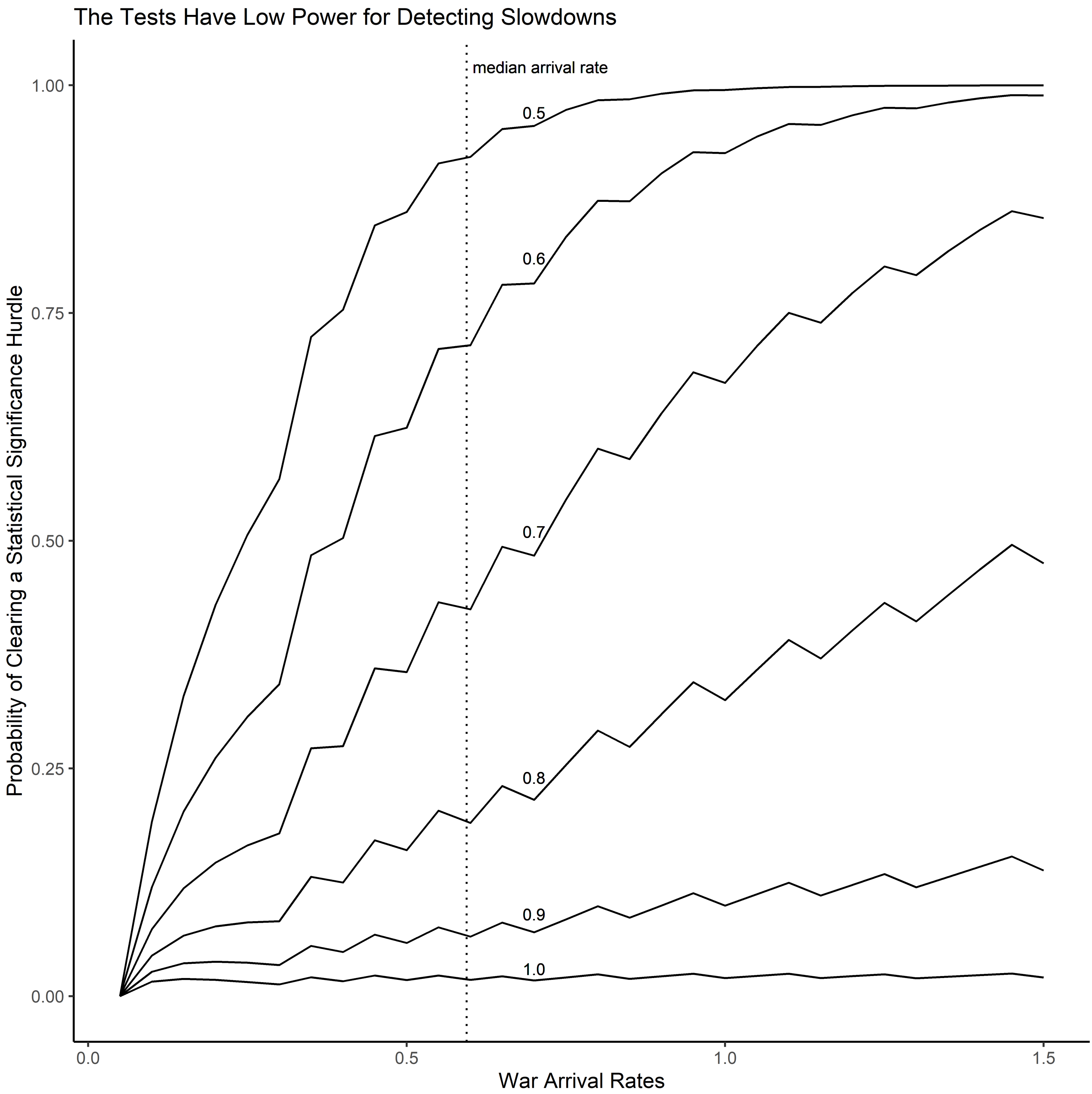

Three Fits to Post-1945 Battle Death Counts with an Unlogged X Axis
CoW Interstate Data
Prob(X > x)
1.00
0.10
0.01
Generalized Gamma
power law
lognormal
0
5000000
10000000
15000000
Battle Death Counts

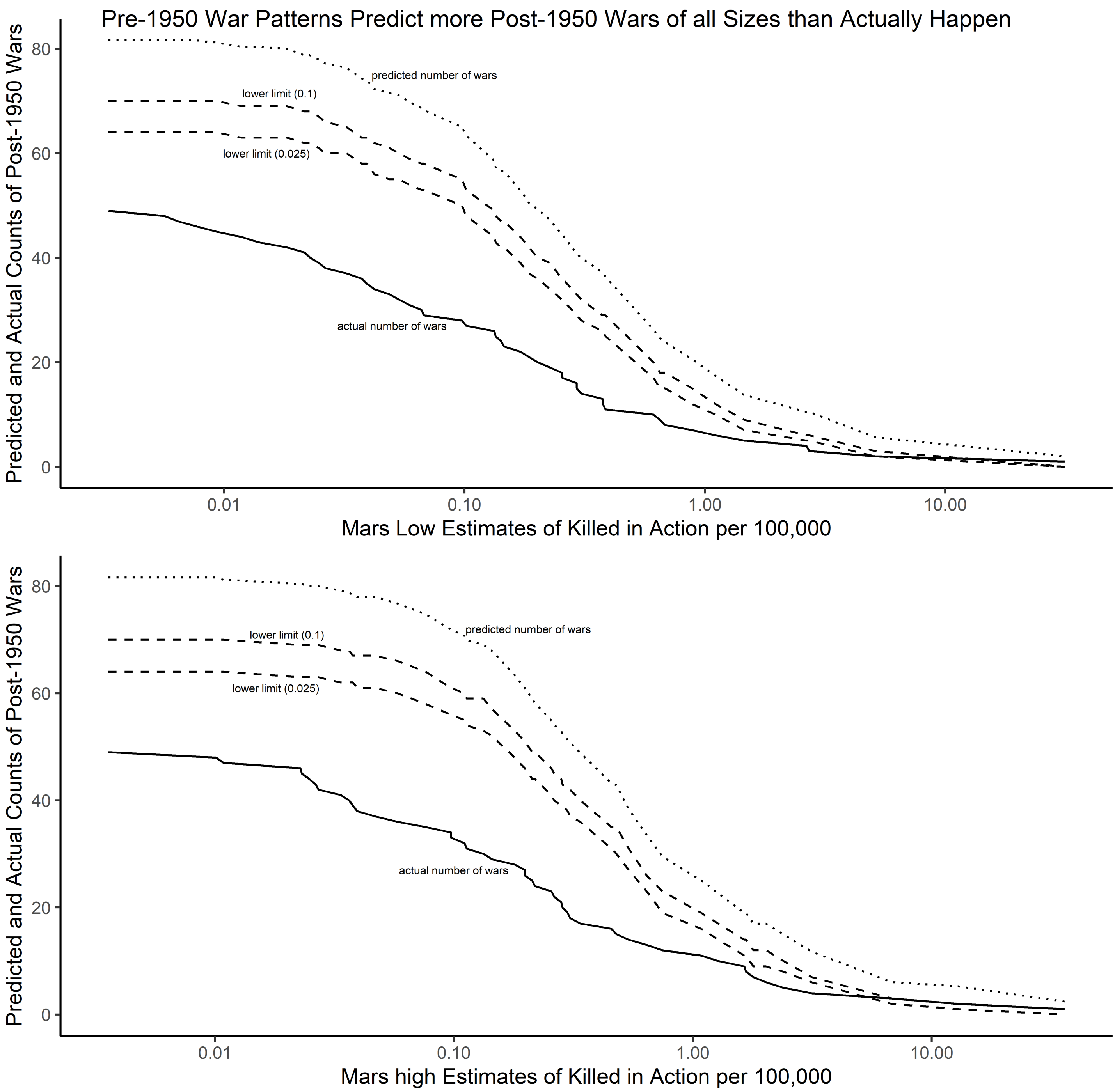

a
Raw Annual Time Series
KIA (low)
20000000
15000000
10000000
5000000
0
1800
1850
1900
1950
2000
Year
b
Annual Deaths with a Logged Y Axis
KIA (low)
10000000
100000
1000
1800
1850
1900
1950
2000
Year
c
The Distribution of KIA Counts on log-log Axes
Prob(X > x)
1.00
0.10
0.01
1000
100000
10000000
Battle Death Counts
Mars Data - Low Killed in Action Estimates

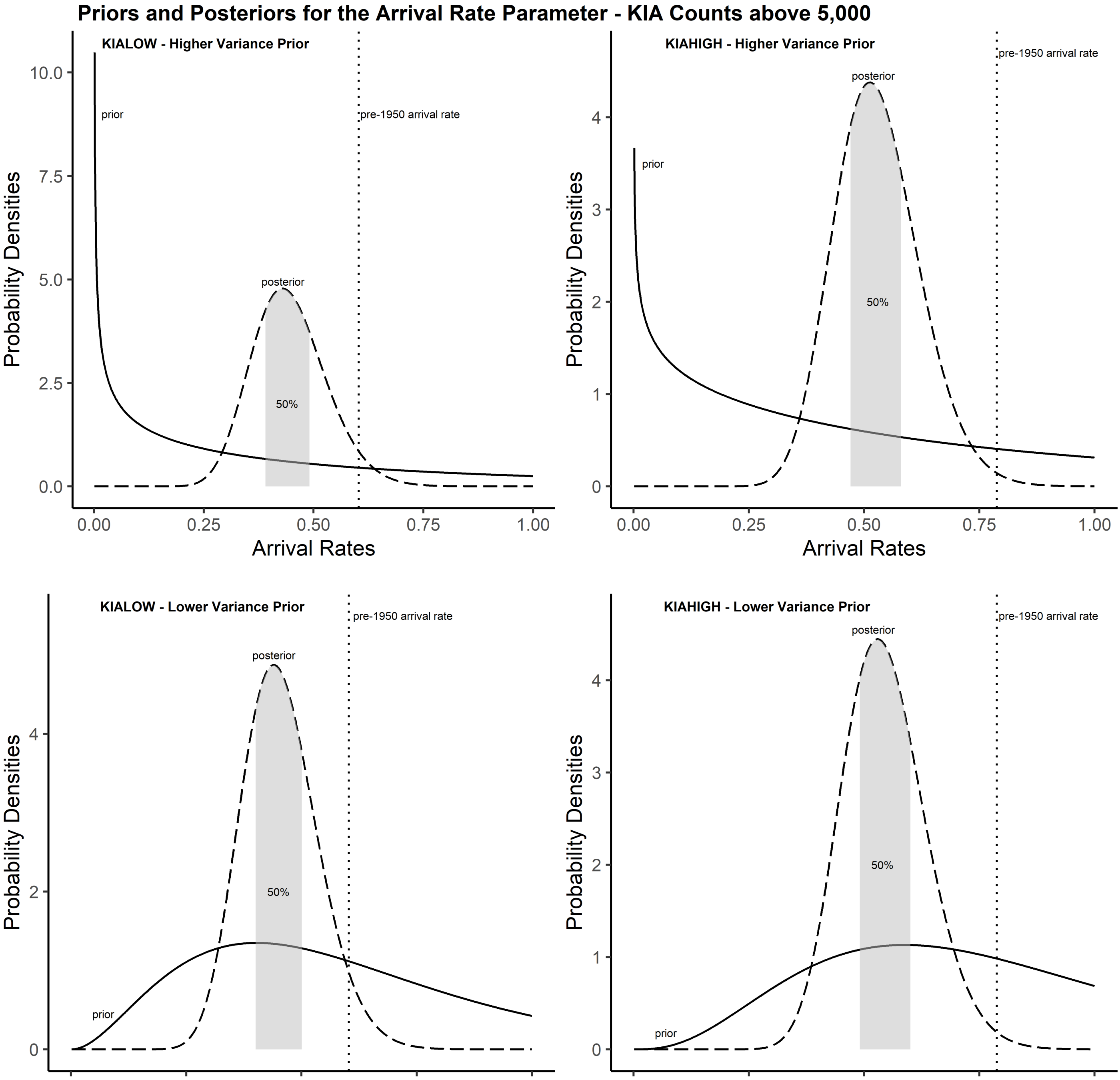
Annualized Averages for Killed in Action from each Year Forward to 2011

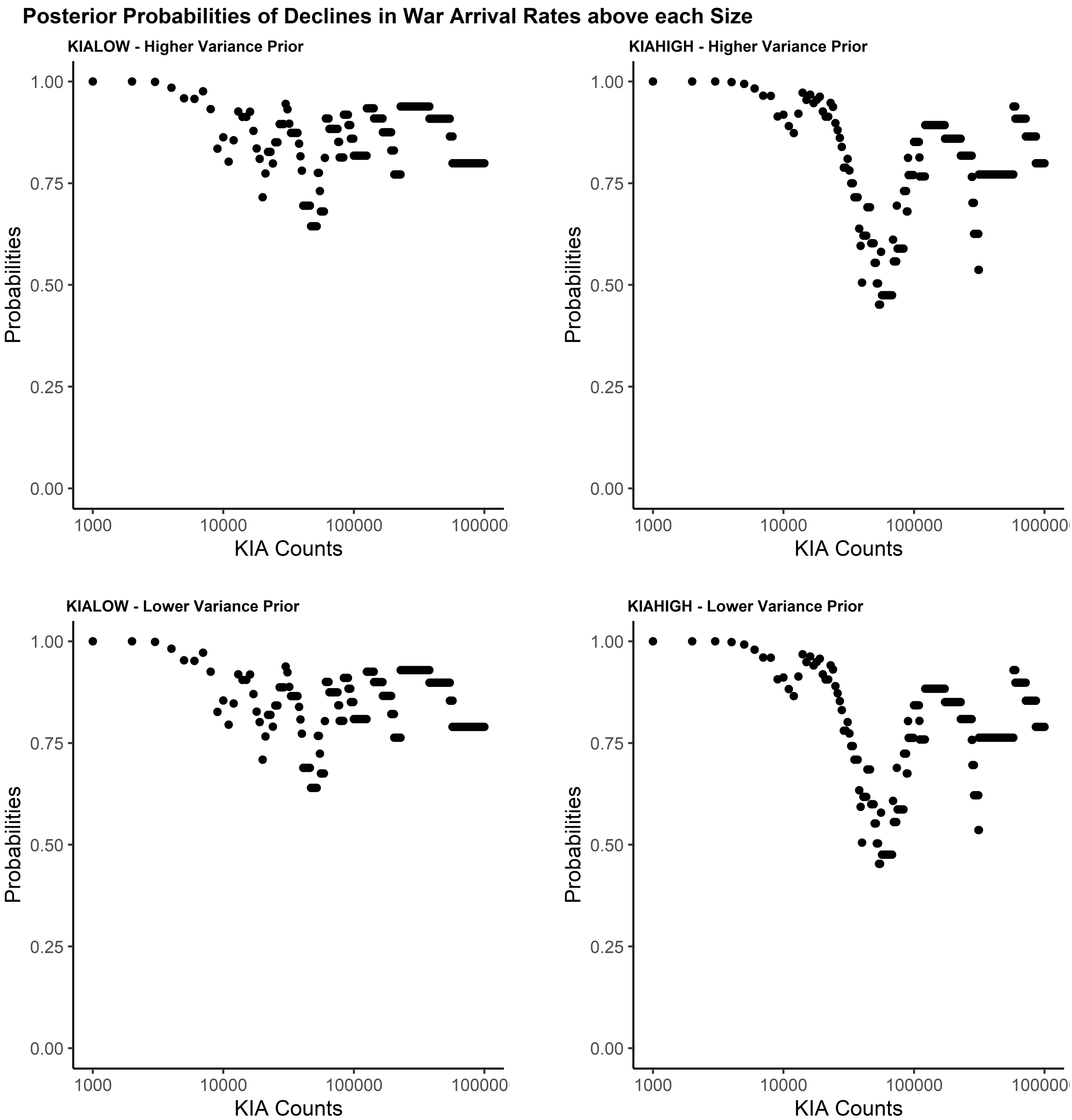


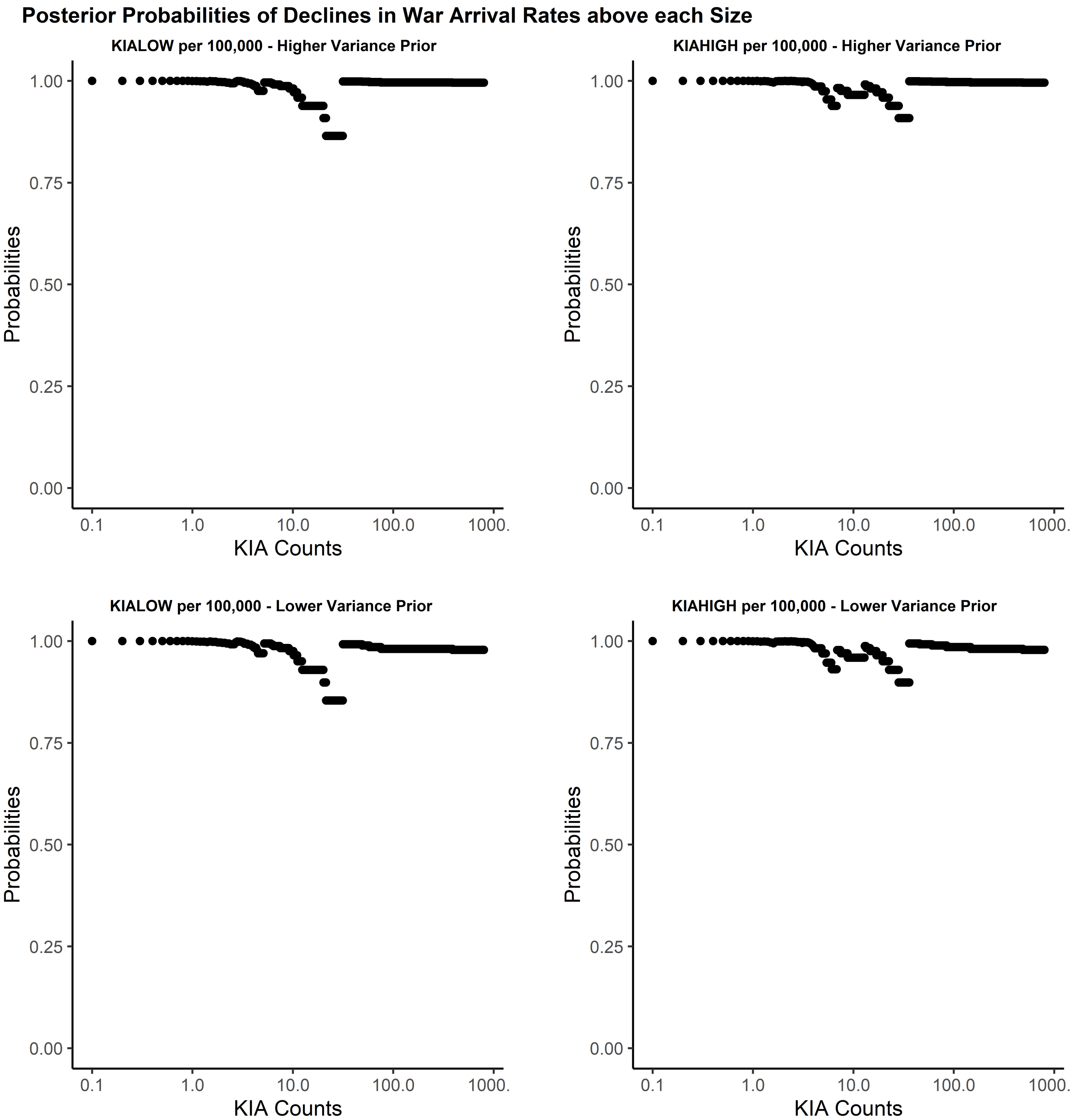

Pre-1950 War Patterns Predict more Post-1950 Wars of all Sizes than Actual
Predicted and Actual Counts of Post-1950 Wars
lower limit (0.1)
predicted number of wars
lower limit (0.025)
actual number of wars
0
20
40
60
80
500
1000
5000
10000
50000
100000
500000
1000000
Mars Low Estimates of Killed in Action
Predicted and Actual Counts of Post-1950 Wars
lower limit (0.1)
predicted number of wars
lower limit (0.025)
actual number of wars
0
20
40
60
80
500
1000
5000
10000
50000
100000
500000
1000000
Mars High Estimates of Killed in Action


The Tests Have Low Power for Detecting Slowdowns
median arrival rate
0.5
0.6
0.7
0.8
0.9
1.0
Probability of Clearing a Statistical Significance Hurdle
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
1.5
War Arrival Rates


Pre-1950 War Patterns Predict more Post-1950 Wars of all Sizes than Actually Happen
Predicted and Actual Counts of Post-1950 Wars
0
20
40
60
80
predicted number of wars
lower limit (0.1)
lower limit (0.025)
actual number of wars
0.01
0.10
1.00
10.00
Mars Low Estimates of Killed in Action per 100,000
Predicted and Actual Counts of Post-1950 Wars
predicted number of wars
lower limit (0.1)
lower limit (0.025)
actual number of wars
Mars high Estimates of Killed in Action per 100,000


Priors and Posteriors for the Arrival Rate Parameter - KIA Counts above 5,000
KIALOW - Higher Variance Prior
prior
posterior
50%
pre-1950 arrival rate
Probability Densities
Arrival Rates
KIAHIGH - Higher Variance Prior
prior
posterior
50%
pre-1950 arrival rate
Probability Densities
Arrival Rates
KIALOW - Lower Variance Prior
prior
posterior
50%
pre-1950 arrival rate
Probability Densities
Arrival Rates
KIAHIGH - Lower Variance Prior
prior
posterior
50%
pre-1950 arrival rate
Probability Densities
Arrival Rates


Posterior Probabilities of Declines in War Arrival Rates above each Size
KIALOW - Higher Variance Prior
KIAHIGH - Higher Variance Prior
KIALOW - Lower Variance Prior
KIAHIGH - Lower Variance Prior
Probabilities
1.00
0.75
0.50
0.25
0.00
KIA Counts
1000
10000
100000



Posterior Probabilities of Declines in War Arrival Rates above each Size
KIALOW per 100,000 - Higher Variance Prior
KIAHIGH per 100,000 - Higher Variance Prior
KIALOW per 100,000 - Lower Variance Prior
KIAHIGH per 100,000 - Lower Variance Prior
Probabilities
KIA Counts
1.00
0.75
0.50
0.25
0.00
0.1
1.0
10.0
100.0
1000.