Enigma*

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Abstract

This paper examines the role of private information in conflict. While acting on information can provide an advantage, using it can expose its source and diminish its value in the long run. I study this trade-off empirically, focusing on the *Battle of the Atlantic* during World War II. There, Allied merchant ships faced Nazi U-boats, which regularly communicated their positions with German central command using Enigma encryption. The Allies secretly broke these codes. I combine novel data on decrypted messages with records of U-boat and merchant ship losses. Using an event-study design, I show that U-boat sinkings of Allied ships fell by 80 percent in the days following position reports, likely due to the rerouting of merchant ships. In contrast, U-boats' own survival declined only marginally. Allied strikes were selective, prioritizing high-capacity commanders and increasing over time—consistent with the Allies strategically forgoing benefits to protect their information access. Counterfactual simulations suggest that military intelligence prevented 40 percent of potential shipping losses.

Keywords: Information in Conflict, Military Intelligence, World War II, Enigma

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1 Introduction

The geopolitical landscape is changing rapidly. From trade to security, long-standing partnerships are being redefined as defense budgets reach historic highs (SIPRI, 2025). Amid these shifts, military intelligence is receiving increased attention. Intelligence consumes vast resources: the United States alone spends roughly $100 billion annually on its intelligence apparatus (US Congress, 2024). While economic research has emphasized the structural determinants of war (e.g. Martin, Mayer and Thoenig, 2008; Caselli, Morelli and Rohner, 2015), the role of information in warfare remains elusive. One might expect it to be decisive, but this view is not self-evident. Actors with superior knowledge face a fundamental trade-off common to many competitive settings: exploiting information can yield immediate benefits, but doing so risks exposing its source to adversaries, thereby diminishing its value in the long run.

Limited evidence on the role of information in warfare is hardly surprising. Intelligence—the collection and use of covert information—is often intangible, with records typically remaining classified for decades. Even if data are accessible, credible inference requires a setting in which the flow of information is plausibly exogenous to concurrent conflict developments.

I overcome these challenges, studying a landmark episode in conflict history: the Allied breaking of the Nazi Enigma. During World War II, the Allies frequently intercepted messages encrypted on Enigma cipher machines. This was particularly important in the *Battle of the Atlantic*—one of the most pivotal campaigns of the war. It staged Allied ships, essential for maintaining supply lines, against Nazi submarines (U-boats). These U-boats often communicated their positions in encrypted radio messages. When the Allies deciphered these codes—which the Nazis believed to be safe—they faced a choice: whether to reroute and save endangered ships, attempt to sink pinpointed U-boats, or to forgo these opportunities, protecting the information source.

I study this choice empirically. I combine newly digitized data from declassified intelligence records with high-frequency U-boat-level event studies. The data reveal how the trade-off in using information governed life-and-death outcomes: intelligence was used extensively to reroute and save Allied merchant ships, but applied selectively to strike against Nazi U-boats, likely to avoid German security upgrades. Using a semi-structural simulation framework, I then quantify the

aggregate benefits of Enigma intelligence in the naval theater. I find that intelligence contributed to saving 421 ships from December 1942 until the end of the war—a 40 percent reduction in losses. In present terms, the benefits, about $16 billion in avoided shipbuilding costs, far outweigh the roughly $1.1 billion spent on intelligence operations.

These results rest on a novel, large-scale data collection effort. Specifically, I digitized the universe of U-boat message decrypts ($n = 43,272$) spanning from December 1942 to the end of the war. To this end, I developed a state-of-the-art machine learning pipeline to extract data from historical intelligence records. This allows me to identify the exact days on which specific U-boats revealed their locations to the Allies. I then link these events with detailed records on all individual Nazi U-boats deployed during the war. Crucially, I observe different states of each U-boat—on patrol, off duty, or sunk—as well as linked records on Allied merchant ship losses. Taken together, these sources allow me to reconstruct the Allied information set in the Atlantic, day by day.

To guide the empirical analysis, I formalize the trade-off in using intelligence through the lens of a simple asymmetric information framework. In the framework, two agents interact: the Allies and the Nazis. The Allies can be of two types, with high or low intelligence capacity, which determines their cost of saving merchant ships or sinking U-boats. In equilibrium, the high-capacity type underutilizes the Enigma advantage to avoid provoking Nazi security upgrades. A key feature of the model is that outcomes are subject to noise and I relate different outcomes to different levels of noise. From the Nazi perspective, variation in merchant shipping was very noisy, reflecting a myriad of different causes. U-boat losses were more precise. Nazis knew with greater accuracy positions, numbers, and operations. The model therefore predicts that the Allies would exercise less restraint in saving ships but more restraint in sinking U-boats.

With this hypothesis in hand, I begin with a motivating piece of evidence. I relate variation in daily code-breaking speed to daily merchant shipping losses and U-boat sinkings. To do so, I hand-collect the exact time required to identify Enigma keys for each day during the years 1944-45 from primary sources. I couple this data with a plausibly exogenous source of variation: a German procedural rule. While Enigma keys were changed daily (Beesly, 1977, p. 66), keys would regularly be changed only partially. So-called 'inner settings' were reused every second day, coinciding with *even* calendar days. Whenever the Germans used such 'paired settings', the number of

remaining potential keys was dramatically smaller (Erskine, 1988; Wright, 2017). In the data, I observe that the Allies were significantly faster in breaking a daily key on even, that is, paired days. The average difference of 8 hours corresponds to roughly a quarter of the mean decryption speed. I argue that if a similar pattern exists in outcomes, it is likely due to the variation in code-breaking speed. The evidence supports this: on even calendar days, 23 percent fewer Allied vessels were hit, while no similar pattern appears in U-boat sinkings.

I interpret this as first suggestive evidence that Enigma intelligence mattered. It also hints at possible restraint in leveraging information with respect to sinking U-boats. But there are two main shortcomings in this exercise. First, it does not directly link information bits with individual-level outcomes. It hinges on the assumption that there are no other sources of cyclical variation that can rationalize a two-day cycle. Second, if the benefits of intelligence emerge with some delay, comparing odd and even calendar days will likely not capture such dynamics.

To address these drawbacks, I rely on much more granular, U-boat-level data. For identification, I employ a stacked event-study design to estimate the effect of Enigma intelligence. The underlying thought experiment is as follows. Compare two otherwise similar U-boats on patrol before and after one of the U-boats reveals its location. Under the assumption of parallel trends, differences in outcomes identify the effect of Enigma decryptions. Two aspects differ from canonical difference-in-differences designs. First, U-boats are typically treated multiple times throughout their lifetime. I therefore use a stacking procedure to isolate each individual treatment event. Second, besides victories over merchant ships, the other main outcome—being sunk—is an absorbing state. Consequently, I can only identify differences in survival probabilities after treatment occurs. By construction, units in both treatment and control groups have not been sunk in the pre-treatment period.

Using this design, I demonstrate that U-boats experienced a sharp reduction in victory rates against Allied merchant vessels following a location revelation. I estimate a decline of roughly 0.72 percentage points for at least five days, relative to a sample mean of 0.89. This implies U-boats lose about 80 percent of their effectiveness once a location message is decrypted. Pre-treatment coefficients close to zero suggest that the parallel trends assumption holds at least before treatment events. Next, I examine U-boat survival probabilities. I find that once U-boat positions are

revealed they experience a highly significant but small reduction in survival probability. After five days, treated U-boats have a 1.1 percentage point lower survival rate relative to the control group. This suggests that, for every 90 decrypted messages with precise geoinformation, only one U-boat was successfully struck.

I argue that part of these seemingly small impacts on U-boat survival are due to strategic restraint—an effort to prevent the Nazis growing suspicious of insecure communications. Consistent with this mechanism, I identify distinct and easily interpretable heterogeneities. Most of the survival reduction stems from sunk high-capacity commanders (defined as above-median victory fixed effects). The asymmetric information framework provides two further testable predictions. First, toward the end of the war, the loss of secrecy looms less large. Hence, restraint should be decreasing over time. The data aligns with this prediction. Location revelations occurring later in the war are associated with relatively larger decreases in U-boat survival rates. Second, if the loss of secrecy carries a greater weight, we should expect greater restraint. I test this under the assumption that disruptions to the Atlantic supply chain were more severe for the UK than for the US. Heterogeneity by geography corroborates this prediction: American forces are more decisive in leveraging decrypts than their British counterparts.

How many Allied merchant ship losses did Enigma intelligence prevent *in the aggregate*? To answer this question, I develop a semi-structural simulation framework. I characterize the different states relevant for U-boats—patrolling, not patrolling, or sunk—as well as transition rates among these states. I then inform the model with the reduced form estimates to simulate counterfactual U-boat distributions. Considering two channels, the short-term reduction in U-boat effectiveness upon a location disclosure and the long-term effect of sinking U-boats, I estimate that Enigma decrypts prevented 421 merchant ship losses, a relative reduction of 40 percent, saving approximately 6,700 seamen's lives from December 1942 until the end of the war.

Counterfactual experiments suggest some untapped gains: had the Allies achieved 1944/45 levels of striking efficiency already earlier or sunk all U-boats with the same decisiveness as the above-median commanders, roughly 80 more ships could have been saved in either case. Overall, however, Enigma intelligence appears to have been leveraged quite effectively.

To evaluate a first-order economic impact, consider that the cost of building a single standard merchant ship, the Liberty, was roughly $1.8 million in the 1940's (Williams, 2014, p. 31) with a present value of roughly $38 million. Preventing the loss of an estimated 421 ships thus implies savings of roughly $16 billion today. Set against the operational cost of Enigma decryption activities—which recent historical research suggests amounted to at least £12 million during the war ($1.1 billion today) (Smith, 2021)—this implies a benefit-cost ratio of roughly 14.6, meaning the intelligence effort generated benefits far exceeding its costs.

Taken together, the evidence shows that well-managed intelligence helped reduce Allied shipping losses by roughly 40 percent—a decisive impact on the Battle of the Atlantic. Beyond conflict, the trade-off between exploiting and preserving information extends to other settings, likely shaping behavior in domains such as innovation, crime, or journalism.

Literature. This paper speaks to different strands of literature. First, it adds to the economics of conflict. Empirical research in this field has examined a wide range of determinants of interstate conflict, including trade (Martin, Mayer and Thoenig, 2008), relatedness of populations (Spolaore and Wacziarg, 2016), natural resources (Caselli, Morelli and Rohner, 2015), recessions (Hess and Orphanides, 1995), political accountability (Conconi, Sahuguet and Zanardi, 2014), and, international alliances (Jackson and Nei, 2015). Most of these studies explore factors that either prevent or initiate conflict. A notable exception is recent work by Federle, Rohner and Schularick (2024), who focus on economic prowess. They find that exogenous financial shocks increase winning odds in military disputes. Building on this literature, I study a hitherto empirically unexplored channel—military intelligence—and provide, to my knowledge, the first empirical quantification of its value in warfare.

Conceptually, the paper links theories of asymmetric information to empirical evidence in the context of armed conflict. Few empirical studies have done so; an exception is work by Fetzer et al. (2021). Their paper interprets insurgent strategy in Afghanistan through the lens of a signaling model. In a similar spirit, I show how the threat of revealing access to Enigma information can help explain life-and-death outcomes in World War II.

I also add to a nascent literature on the effects of covert intelligence. Within this realm, Sonin and

Wright (2024) show that enhanced surveillance capacity is associated with more complex tactics and greater effectiveness against security forces in Afghanistan. Their measure of intelligence, however, is based on surveillance operations that were *exposed* by the other conflict party. This differs from the setting studied here, where the Nazis never realized that Enigma keys had been broken. Another pioneering study is Glitz and Meyersson (2020) who find that industrial espionage during the Cold War raised East German productivity. Distinct from both studies, I do not only focus on direct benefits but also highlight the indirect limits of information that arise from dynamic considerations. In doing so, I address both first-order and second-order effects in the use of intelligence.

Moreover, I contribute to research on the determinants of conflict outcomes in World War II. Most existing work on this theme examines individual motives and behavior downstream. For example, Ager et al. (2022) study peer effects among fighter pilots in World War II, while Adena et al. (2021) explore how bombings and the destruction of hometowns affected pilots' morale. Rozenas, Talibova and Zhukov (2024) investigate the role of state repression on soldier motivation. In contrast, my focus is on decisions made at the highest levels of the Allied command, where strategic use of intelligence could, and arguably did, shape the course of the conflict.

On a final note, this paper relates to a tradition of economists devoted to applied research in World War II (Guglielmo, 2008). Famously, the Statistical Research Group, with members such as Harold Hotelling and Milton Friedman, aided the Allied war effort devising methods of submarine search (Wallis, 1980). I contribute new perspectives on strategic decision-making at the highest levels of command.

Outline. The paper unfolds as follows. First, I provide a broad overview of the historical background in Section 2. Section 3 formalizes the key trade-off involved in weighing the use of intelligence. I then discuss data sources and construction in Section 4. Section 5 explains the empirical strategy and presents estimation results. Section 6 sets up the simulation framework and evaluates aggregate effects. Finally, Section 7 concludes.

2 Historical Background

Enigma. All major powers in the Second World War used machines to encrypt communication. The Germans predominantly relied on so-called Enigmas, with different versions and networks active across theaters of war.[1] Enigmas, at their core, were rotor machines. A given plaintext would be transformed letter by letter, depending on underlying settings. Appendix Figure A1 provides a simplified illustration of the mechanics. The receiver could then decode these texts knowing the correct settings. Identifying these daily changing settings was the key obstacle in Allied decryption efforts.

Intelligence officers employed various methods to break codes. The predominant technique relied on so-called cribs, small bits of guessed plain text, which allowed the reconstruction of keys. Commonly used cribs pertained to routine weather reports. For instance, specific messages consistently started with "VONVONWEWABOULOGNE" (From weather station Boulogne).[2] Matching the guessed plaintext with the encrypted letter sequence, electro-mechanical machines[3] then helped identify the underlying Enigma configurations by iteratively eliminating incorrect settings (Sebag-Montefiore 2000, p. 151-153; Budiansky 2000, p. 131).[4]

Initially, the Allies lacked the capability to decrypt U-boat messages. That changed in May 1941, largely by chance (Beesly, 1977, p. 71). The Allies successfully recovered codebooks from a conquered U-boat, allowing for real-time decryption over several weeks. More importantly, this episode helped code-breakers to learn, and to identify patterns, that would allow codes to be broken even in the absence of current codebooks. While an Enigma security upgrade disrupted Allied decryption efforts in February 1942, this setback was overcome by December 1942 (Budiansky, 2000, Appendix A). From that date until the end of the war, U-boat codes were often broken within a few hours or days.

Typically, messages were intercepted at different stations around Atlantic coastlines (Syrett, 1999)

[1] Hinsley (1981, Appendix 4) provides an exemplary overview of different keys attacked by British cryptanalysts in the earlier half of WWII.

[2] In some instances, the Allies provoked Germans to send cribs unknowingly. For instance, the Royal Air Force was instructed to lay mines in designated regions prompting specific message responses (Sebag-Montefiore, 2000, p. 187).

[3] These machines, called 'bombe', were initially developed by Gordon Welchman and Alan Turing (Erskine, 1989).

[4] For precise accounts of the technical aspects of Enigma encryption and decryption I defer to Sebag-Montefiore (2000, Chapter 3), Kahn (1991, Chapter 7) and Budiansky (2000, Chapters 2&4).

and relayed to Bletchley Park, a country house north of London, where the bulk of decryption activities were handled.[5] Intercepts, even without the decrypted text, often already carried valuable information. Using direction-finding (DF) methods radio signals could indicate rough locations of vessels.[6] However, this required several independent bearings from different stations. Moreover, signal characteristics like the length and format could indicate what type of message was being sent, e.g. a convoy sighting or a weather report (Syrett, 2002). In some instances, it was even possible to identify U-boat radio operators solely through their morse-sending style (Beesly, 1977, p. 272-273).

Once settings were broken, messages were translated and sent to the Operational Intelligence Center (OIC) in London. This was where decisions were made on how to respond to novel intelligence (Beesly, 1977, p. 61-72). Roughly one third of all decrypts that arrived at the OIC contained specific information on U-boat grid positions.[7] Typically, these allowed for pinpointing vessels to 11 by 11km squares (Erskine, 1992). Appendix Figures A2 and A3 provide examples of Nazi grid maps.

U-boat warfare. In the study at hand, I focus on U-boat warfare, later referred to as the Battle of the Atlantic. The naval theater saw the longest war campaign in WWII. The Allies were shipping vast amounts of goods and resources, mainly from the Americas to the UK, later on also to the Soviet Union, while German submarines sought to intercept and destroy these merchant vessels. Control over the Atlantic sea lanes was vital. As Churchill (1952, p.6) famously noted,

> "[t]he Battle of the Atlantic was the dominating factor all through the war. Never for one moment could we forget that everything happening elsewhere, on land, at sea, or in the air, depended ultimately on its outcome, and amid all other cares we viewed its changing fortunes day by day with hope or apprehension."

Throughout the war, over three thousand ships were sunk by Nazi U-boats, of which 2750 were

[5] Later in the war, Americans joined the decryption efforts. Intelligence among the Allies was generally shared on a high-frequency (Syrett, 1999). Kohnen (1999) provides an in-depth account of Anglo-American intelligence cooperation.

[6] The typical accuracy of DF estimates was an area of approximately 10,000 square miles (e.g. 100 by 100 miles) (Beesly, 1977, p. 272)

[7] Own calculations based on all U-boat messages decrypted from December 1942 until May 1945.

merchant and passenger ships. While German submarines were, by and large, the main threat against Allied vessels, both the Japanese and Italian Navies also deployed submarines in warfare. While the Italians sank 99 merchant vessels, predominantly in Mediterranean waters but also in the Atlantic, the Japanese accounted for roughly 244 sinkings.[8]

Concealing the secret. The Allies went to great lengths to maintain the secrecy of Enigma's vulnerabilities. Besides staff at Bletchley Park, only a few dozen individuals in the leadership of the Royal Navy and the US Navy had access to Enigma-derived intelligence (Beesly 1977, p. 99, Knowles 1977, Kohnen 1999, p. 78).

In the Atlantic, it was Admiralty directive that the "source must never be jeopardized by carrying out a tactical operation which might arouse the enemy's suspicion".[9] Whenever intelligence was shared, the Allies were meticulous in creating plausible alternative explanations for successful operations. In some instances, Enigma information was reportedly only acted upon, if Air Reconnaissance activities or precise direction-finding fixes had also revealed a particular position (Knowles, 1977; Beesly, 1977, p. 90 & 101). At times, BP officials instructed the Admiralty to specifically refer to Air Recce as the source of success when talking to the press (Batey, 2011). The British also spread the rumor that they had developed a novel radar technology capable of detecting U-boats at very large distances (Hinsley, 1990).

Necessitating such *plausible deniability* raises the question of to what extent Enigma intelligence was deliberately not acted upon when alternative sources were missing. Here, the historical literature is surprisingly scarce. To the best of my knowledge, a systematic account does not exist. In one rare instance, after a series of successful attacks, Andrew Cunningham (1944), First Sea Lord, was quoted as stating "that for the present it will be most advisable to suspend operations against U-boats" (as cited in Kohnen, 2019). It is unclear, however, to what extent this thinking guided intelligence utilization throughout the war.

Historian Ralph Bennett, who also served at Bletchley Park, underlines this mechanism albeit in a different theater, Axis supply lines in the Mediterranean. He contemplates why not more

[8] Numbers are based on `https://uboat.net/` and Rohwer (1999). Warships etc. are excluded.
[9] ADM 223/88, "Admiralty Control in Operations."

Axis tankers were sunk with the help of decrypted messages, concluding "[s]ecurity measures to protect the source are perhaps the most likely explanation" (Bennett, 1996).

Ex-post, worries of revealing the compromise were indeed merited. In several instances, German officials became highly suspicious of cipher leakages, particularly after successful strikes on U-boats. Yet, despite internal investigations, it was never concluded that broken Enigma codes were the cause (Erskine and Weierud, 1987; Ratcliff, 1999).[10] Along this vein, it remains noteworthy that it took almost three decades until the secret of the compromise reached the public, a fact that also greatly surprised the late German U-boat admiral, Karl Dönitz:

> "So that's how it happened!... I have been afraid of this time and again. Although the experts continually proved—with conviction as it seemed—that there were other reasons for the suspect observations, they were never able to dispel my doubts completely... Only after the war did I feel reasonably reassured by the lack of any reports from the Allied side... Well, now you historians will have to start right at the beginning again!"[11]

3 A Simple Model

To guide the empirical analysis, I begin by formalizing the key trade-off associated with exploiting intelligence.[12] I also develop auxiliary predictions, which I later test in the data. Details and derivations are provided in Appendix Section B.

I consider a standard asymmetric information game with two agents: the Allies and the Nazis. The Allies may be one of two types, high-capacity (θ^H) or low-capacity (θ^L), with the high type able to leverage superior intelligence capabilities. I conceptualize being the high type as having a lower cost in achieving desirable military outcomes (e.g., saving merchant ships or sinking U-boats). The probability p of being the high type is common knowledge.

[10] Even in 1970 a German intelligence officer still publicly sustained the claim that U-boat ciphers were never broken (Ratcliff, 1999).

[11] Transcribed in the foreword by Jürgen Rohwer in the 2012 edition to Dönitz (1958) memoirs.

[12] To the best of my knowledge, strategic restraint in intelligence utilization has not been formally micro-founded. Axelrod (1979) characterizes the use of intelligence, but as a one-agent problem assuming that 'intelligence' can only be used once and is lost thereafter.

The game unfolds over two periods. In the first period, the Allies choose action s_1, which can be interpreted as the number of merchant ships they wish to save, or U-boats to sink. The Nazis then observe signal $z = s_1 + \varepsilon$ representing the realized number of saved ships/sunk U-boats, subject to additive noise. The noise term ε is uniformly distributed with boundaries $[-\phi/2, \phi/2]$.

Given the signal, the Nazis decide whether to invest in a costly security upgrade, or not. If the investment is made, the Allies' cost structure becomes that of the low-type in the second period, regardless of the initial type assignment. Else, they retain their original cost structure. After the Nazi decision, the Allies choose s_2—the number of merchant ships they wish to save or U-boats to sink—in the second period. From the perspective of the first period, the second period is discounted at rate β. Finally, note that Nazi payoffs in the first period are unaffected by their upgrading decision, but they linearly dislike increasing levels of s_2 in the final period.

I define an equilibrium as a set of strategies by Allies and Nazis that constitute best responses to each other along with beliefs held by Nazis that map all signals to a Bayesian posterior over the Allied type. Under parameter assumptions that permit an interior solution, the following characterizes equilibrium behavior. The Nazis adopt a cutoff rule: they choose to make the costly security investment only if their Bayesian posterior that the Allies are high-type is sufficiently high. Concretely, they upgrade if the Allies save very high numbers of ships or sink unusually many U-boats. The high-type Allies, aware of this upgrading behavior, strategically reduce s_1 in the first period—relative to a hypothetical optimum in a single-period model—to probabilistically avoid triggering the investment. This behavior captures the notion of restraint in the utilization of intelligence.

The model generates three testable predictions.

1. **Restraint decreases with noise.** Consider rerouting merchant ships and sinking U-boats separately. The Nazis are fully aware of their U-boats, their states, positions, etc. whereas their knowledge of merchant ships is much more limited. It is unclear how many there are, and under what conditions they are operating, making it far more difficult to accurately assess how many should be expected to sink. I conceptualize these differences by allowing the variance of the noise level ε to vary by outcome. Comparative statics predict greater

restraint in using intelligence to sink U-boats, but less restraint in rerouting and saving merchant ships as the noise support increases.

2. **Restraint declines over time.** The parameter β can be interpreted as the relative weight of the future. The weight is larger when the second period is 'longer'. Comparative statics predict that, earlier in the war, more information is strategically left unused than in later stages.

3. **Restraint increases in the relative value of retaining/losing Enigma intelligence.** With a minor extension of the baseline model, one can introduce a parameter that shifts the value of saving ships or sinking U-boats in the second period. I relate this to differing valuations of the stakes by British versus American forces. Arguably, disruptions to the Atlantic supply chain loomed relatively larger for the British. Comparative statics predict greater restraint when the relative valuation is higher. We would therefore expect British forces to exploit intelligence less.

4 Data

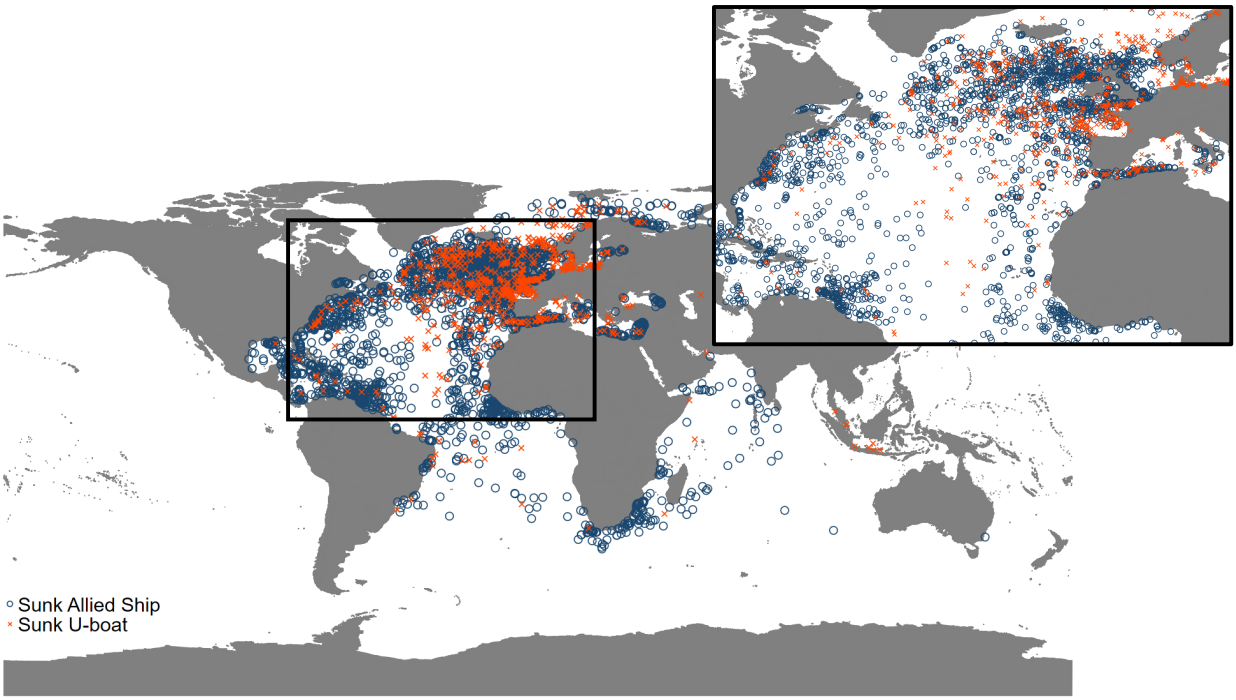
To test these predictions and to perform an aggregate quantification exercise, I collected extensive data on naval warfare and intelligence. This includes information on naval vessels (Allied merchant ships and Nazi U-boats) as well as novel data from messages encrypted with Enigma machines. This section discusses the data sources, describes the construction of the dataset, and presents descriptive statistics.

4.1 Naval Vessels

The primary source of data on naval vessels is https://uboat.net/, accessed in mid-2023. The website has compiled and digitized extensive information on units related to naval warfare in World War II. The data are based on a large body of authoritative historical works and archival material from the German U-Boat Museum, which have been systematically cross-referenced by a group of dedicated naval history enthusiasts. I have also manually checked selected database

entries with Rohwer (1999), work by a renowned German military historian, concluding that data quality is very high. In total, the records cover 3,335 Allied ships sunk by Nazi U-boats.[13] To provide a sense of the geographic scope, Figure 1 illustrates the distribution of sinkings, with most occurring in the North Atlantic. For most ships, I observe the date on which a hit occurred, the associated tonnage, and the number of lives lost. For auxiliary purposes, I also gathered information on ships sunk by other Axis powers, the Japanese and Italian navies.[14]

Figure 1: Geography of the U-boat warfare.



Notes: Circles represent locations of hit Allied merchant ships by a Nazi U-Boat. Crosses indicate sunk U-boats.

For the main analyses, I restrict the data in two ways. First, I focus only on merchant and passenger ship losses ($n = 2,750$), because their objectives were clearly defined: the Allies aimed to minimize losses, while the Germans sought to maximize them. This excludes primarily warships, where associated losses are more difficult to interpret (e.g. when they result from protecting merchant vessels).[15] Second, when analyzing aggregate variation in Allied decryption capacity specific to

[13]This includes 80 events in which a vessel was heavily damaged, but not sunk, and 6 captures. For ease of exposition, I refer to all these events as "ship losses".

[14]For Japanese submarines, I digitized information from Rohwer (1999) while data on Italian submarines were also collected on `https://uboat.net/`.

[15]In some instances, escort vessels were intentionally sacrificed (Beesly, 1990).

the U-boat network, *Shark*, I restrict the sample to vessels operating in regions covered by the network. For example, I exclude merchant ships sunk by U-boats in the Mediterranean after June 1943, as these U-boats moved to their own, separate network. Notably, these geographical restrictions remove only a small fraction of sunk merchant vessels (4.1 percent).[16] However, when relying on U-boat-level variation, I do not impose geographic restrictions.

Ideally, I would also like to observe the total number of merchant vessels sailing at a given point in time—not only those that were lost. Unfortunately, I am unaware of an accessible database that records all successful WWII merchant voyages. As an imperfect measure, I collected data on the main official convoy voyages from the online compendium to Rohwer and Hümmelchen (2005).[17] The limitation is that this only represents a subset of all active voyages. It does not include independently sailing merchant vessels. To give a sense of the scale of missing voyages: among all merchant ship losses, there was a roughly equal split between independently sailing ships and those in convoy groups. Summary statistics of key variables in the time series are presented in Table 1. Across the entire war, 1.27 merchant ships were sunk every day, while close to 700 ships sailed daily in convoy groups.

I also collected extensive information on all Nazi U-boats from `https://uboat.net/`. For each unit, I observe key events, including fleet entry, active patrol periods, and ultimate fate (sunk or survived). On average, around sixty U-boats were active on a given day during the war, with one U-boat lost every three to four days in Shark-designated waters (Table 1). Importantly, for each U-boat I observe associated kills/victories over Allied ships. For 85 percent of U-boat-day observations, I also obtained geographic positions. In case of incomplete location data, I impute missing positions using the last known coordinates.

For the main analysis, I construct a granular panel dataset at the U-boat-day level. I focus on all units on active patrol—the key object for understanding the operational impact of Enigma intelligence—from December 1942 to May 1945. During this period, U-boat codes were broken with high frequency and little delay. In total, I observe 676 U-boats going on at least one patrol (Table 2). The average U-boat commences five patrols, sinking one merchant ship over the sample

[16] The precise selection process is detailed in Appendix C.1.

[17] Data accessed in late 2022 on `https://www.wlb-stuttgart.de/seekrieg/konvois/konvois-frames.htm`. These are digitized tables from Hague (2000).

Table 1: Summary Statistics (daily time series).

	Mean	SD	Min	Max	N
Sunk merchant ships	1.27	1.89	0	15	2074
Merchant ships sailing	686	256	0	1,421	2074
Sunk tons	6,798	10,813	0	96,906	2074
Sunk U-boats	.284	.67	0	9	2074
Patrolling U-boats	59.5	37.6	2	158	2074

Notes: Summary statistics of the time series data set. Unit of observation: day. Coverage: September 1939 - May 1945, Shark regions.

period. However, this average masks considerable heterogeneity. U-181, for instance, recorded fifteen merchant ship victories, U-510, a staggering eighteen.[18] Both U-boats also remained operational until Nazi Germany's surrender. Yet, these were far from common outcomes, nearly three-quarters of all U-boats were destroyed before Allied victory (Table 2).

Table 2: Summary Statistics of U-boats active December 1942 to May 1945.

	Mean	SD	Min	Max	N
No. patrols	4.98	4.61	1	35	676
Days patrolling (tot.)	112	93.9	2	520	676
Days location msg. decrypted	11	11.8	0	62	676
Days other msg. decrypted	17	17.1	0	101	676
Sunk merchant ships	.994	1.95	0	18	676
U-boat lost	.731	.444	0	1	676

Notes: Summary statistics for all patrolling U-boats. Coverage: December 1942 - May 1945.

Time trends. How does decryption capacity co-move with naval outcomes over time? I provide a birds-eye view in Figure 2. In Panel (a) I show monthly averages of sunk Allied merchant ships while Panel (b) shows Nazi U-boat losses. Dashed lines track the number of active merchant vessels in (a) vis-à-vis the number of patrolling U-boats in (b).[19] Both panels also display periods in which the Allies were able to break U-boat Enigma codes as light blue backgrounds.[20]

Allied cryptanalysts first managed to break U-boat ciphers in May 1941. Subsequently, traffic was read over several months with little delay. In Figure 2, perhaps surprisingly, we observe little

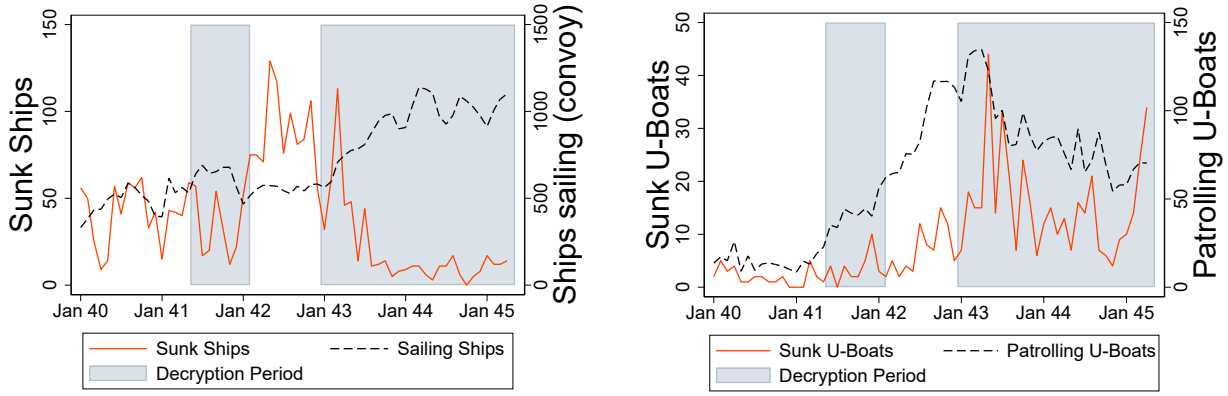
[18] Numbers relate to the sample period.
[19] Active merchant vessels are those sailing in convoy.
[20] Precise dates are drawn from Beesly (1977, p.71) and Budiansky (2000, Appendix A).

outcome variation around the first breaking of codes. Neither does the number of sunk merchant ships decline dramatically, nor does the number of sunk U-boats increase markedly. A plausible reason: the Allies first underwent a period of learning.

In February 1942 the Germans suddenly changed their encryption system. As a result, decryption efforts were rendered unsuccessful for approximately ten months. During this time outcomes appear to respond. German merchant sinking rates increase two to three-fold—Nazis later referred to this period even as "the happy time". Somewhat unintuitively, the number of U-boat losses also increased in this period. A likely cause was the simultaneous release of more U-boats into patrol.

Finally, on the 14th of December 1942, the Allies eventually learned how to solve keys for the new, improved Enigma system. From one day to the other, codes were again broken with short delays, and information was immediately translated into operational usage. At the same time, losses of merchant ships declined substantially from previously almost one hundred ships per month to less than twenty. U-boat losses continued to grow for some time and remained at a relatively high level until the end of the war.

Figure 2: Sunk merchant ships and U-boats over time.



(a) Sunk merchant ships

(b) Sunk U-boats

Notes: Left-hand panel presents the number of sunk merchant ships and ships sailing in convoys binned by months. The right-hand side shows the number of sunk and patrolling Nazi U-boats binned by months. The shaded areas indicate periods in which Enigma messages were largely decrypted. The corresponding shares of sunk ships and U-boats are presented in Appendix Figure D1.

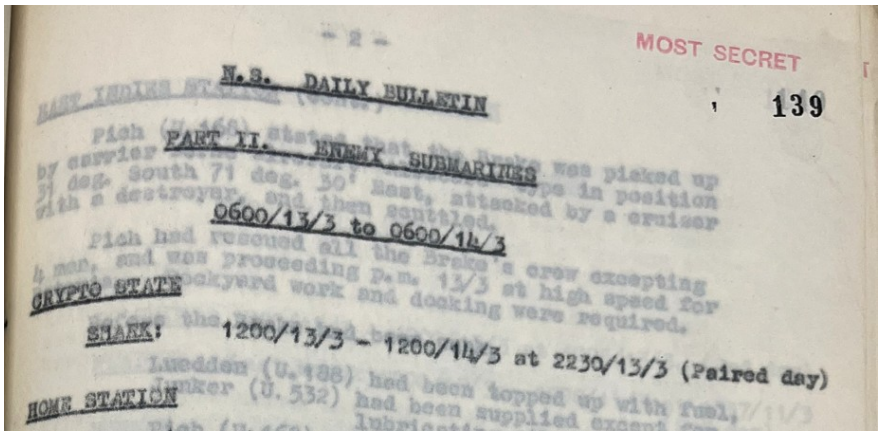
These aggregate patterns suggest co-movement in decryption capacity and naval conflict out-

comes. One may be tempted to infer a causal relationship, but there are several concerns. Most importantly, confounding events were occurring around key dates. For instance, higher merchant and U-boat losses in 1942 relative to before may be a result of the US officially entering the war, not the Enigma upgrade. To obtain credible causal estimates and to shed light on predictions derived in Section 3, I draw on high-frequency microdata which I discuss next.

4.2 Enigma Intelligence

My key data contribution is the collection and digitization of Enigma intelligence. I explore two sources. First, I focus on an intensive margin, i.e. how fast daily keys were broken. Specifically, I collect data from daily naval bulletins held at the National Archives, Kew, London. Figure 3 provides an example of a bulletin entry. For close to each day starting on the 15th of November 1943 until German surrender these records allow me to compute the number of hours the Allies required to break a new daily key. I use this type of variation to provide motivating evidence on the importance of Enigma intelligence.

Figure 3: Example of daily breaking time.



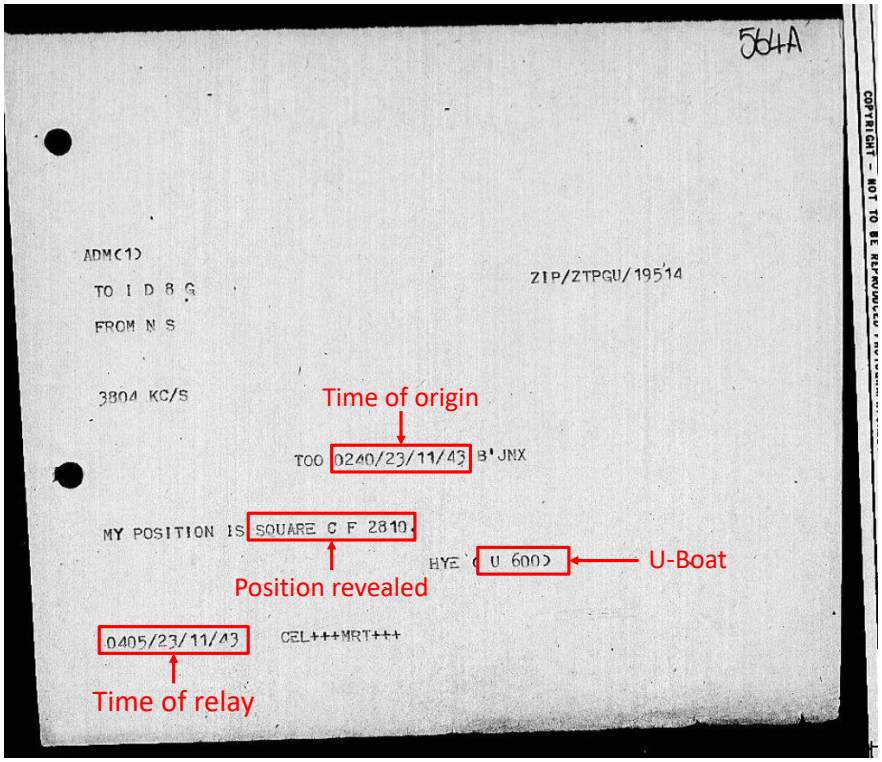
Notes: Excerpt from the N.S. Daily Bulletin documenting that the Shark (U-boat) key for the 13th of March 1944 (to 14th) was broken at 22:30 on the 13th of March (National Archives, Kew: HW 8/2).

The second source, which gives me even more granular variation, comes from original decrypted messages. I collected all U-boat decrypts from the National Archives from December 1942 until May 1945. This includes 43,272 scans available online.[21] Using state-of-the-art object detection,

[21]Besides the National Archives in London, the National Archives at College Park, Maryland (USA) also hosts an

I first segmented unstructured decrypt layouts. I then applied optical character recognition software (OCR) and eventually extracted key information bits: (1) specified U-boats (or their associated commanders) (2) time of interception/origin (3) time of record entry/information forwarded to the OIC and (4) marker for inclusion of geo-information. While Appendix C.3 discusses the digitization process in greater detail, Figure 4 presents an annotated decrypted message.

Figure 4: Decrypt example.



Notes: Sample decrypt with highlighted extracted information. (Source: National Archives, Kew, DEFE 3/724/576).

After text processing, I matched decrypts day by day with all 676 U-boats patrolling from December 1942 to May 1945. In the aggregate, about 30 percent of messages carry location information. Matched with the U-boat panel, I code roughly ten percent of patrol days as days with revealed locations (Table 2).

archive of decrypts. In practice, these share the information content (Syrett, 1998, p. xxiii). The reason I still collected data from the British source is their digital availability.

5 Empirical Analysis

In this section, I characterize how Enigma intelligence shaped naval war outcomes. First, I begin with motivating evidence, drawn from daily variation in code-breaking speed. Second, in the main analysis, I leverage variation from decrypts that differentially reveal U-boats. These estimates then inform the aggregate quantification exercise.

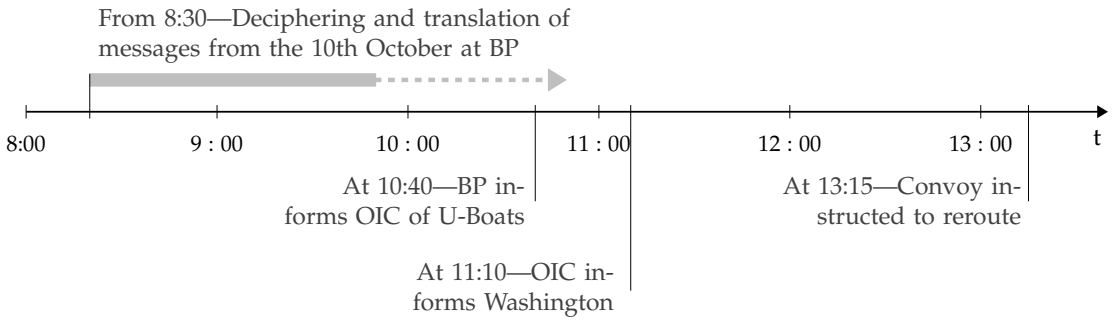
5.1 Motivating Evidence

Does the timely arrival of intelligence matter? To set the stage for a first empirical answer it is instructive to narrate a few days in the journey of convoy SC48 based on the account of Rohwer (1979).

Case study. Convoy SC48 started its journey on October 5, 1941, heading from Nova Scotia, Canada, toward Liverpool. Initially uneventful, the situation changed on October 12 (timeline illustrated in Figure 5). That morning, Allies had decrypted the October 10 daily key and cryptanalysts immediately began deciphering and translating messages at Bletchley Park (BP). At 10:40 am BP then relayed pivotal information to the OIC confirming the position of four Nazi U-Boats in threat of encountering SC48. Only thirty minutes later, British authorities advised Washington to reroute the convoy, which the U.S. did by 1:15 pm, ensuring the convoy's temporary safety. Within hours of a recent key break, relevant information was extracted, and operational actions were almost instantly taken.

However, convoy SC48's journey was not over yet. A few days later, on the 15th of October, the convoy encountered U-553 by chance and three vessels were subsequently lost. Instructions to U-553 and surrounding U-boats had been decrypted 26 hours too late. This episode exemplifies the importance of *timely* decryption. Next, I will quantify its importance.

Figure 5: Timeline on the 12th of October 1941.



Notes: Communication chain on the 12th of October 1941. Based on Rohwer (1979).

Variation. To this end, it is useful to begin by thinking about the ideal design. In an experimentally controlled environment, one would consider the following equation:

$$y_t = \alpha + \beta DecryptionTime_t + \varepsilon_t \tag{1}$$

where y_t are sunk merchant vessels/U-boats and $DecryptionTime_t$ is a randomly varying time lag in the identification of day t's encryption settings. In this design, β would capture the causal effect of decryption time on respective outcomes, and we would expect lower time lags to be associated with lower merchant losses/ higher U-boat sinking. The concern with estimating the β coefficient in the setting at hand is, however, that decryption time is not necessarily random. In particular, effort and computation power, which directly affected how fast a codes were broken, were reshifted among Enigma keys depending on need, as discussed by Rohwer (1988, p. 91), Erskine and Marks (2004), and Kohnen (2019, p. 281). To the extent that more effort was exerted on riskier days, a lower decryption time might even be associated with higher merchant losses.

To solve the endogeneity problem, I rely on a simple reduced form exercise. I draw on a procedural rule in German code-changing behavior. Settings of the naval Enigma were divided into two components: inner and outer. German procedures stipulated that while the outer component should change every day, the inner component should only change on *odd* calendar days (Erskine, 1988). It is not entirely clear why this rule existed, but a likely reason was that the inner component was only to be updated by higher-ranking officers in an effort to increase security. Crucially, this meant that on every *even* calendar day, the inner component was reused from the previous day.

When settings were "paired" it was substantially easier for Allied cryptanalysts to decrypt Enigma codes (Erskine 1988; Budiansky 2000, p. 157; Wright 2017).

I use this cyclical rule as a source of regular and exogenous variation for decryption speed. I argue that if we observe a similar two-day cycle in conflict outcomes, it is likely because of the cyclicality in code-breaking speed.

Evidence from two-day cycles. In the data, I first document that even calendar days had significantly faster decryption speed. Mean decryption times are depicted in Figure 6 Panel (a). I find that there is a substantial difference (8 hours) across even and odd calendar days, that corresponds to roughly a quarter of mean decryption speed (30 hours).[22] Reassuringly, the same pattern exists in the decrypt-level data (Appendix Table D2). For the decrypts, I calculate the time span from interception to being relayed to the OIC. Again, I estimate a 22-23 percent time drop from odd to even days. Importantly, this variation is mirrored in the share of messages decrypted exceptionally fast ($\leq$ 12 hours). The share amounts to 23 p.p. on odd, but 29 p.p. on even calendar days, a 23 percent difference relative to the mean.

I then proceed by showing that such a two-day cycle also exists in the number of sunk merchant ships: on even calendar days, significantly fewer Allied vessels were hit by German U-Boats (Figure 6 Panel (b)).[23] I estimate a difference of about 23 percent of the mean shipping losses per day, which is equivalent to one more saved ship every six days. Reassuringly, I do not identify such a two-day pattern in periods where Enigma codes remained unbroken.[24]

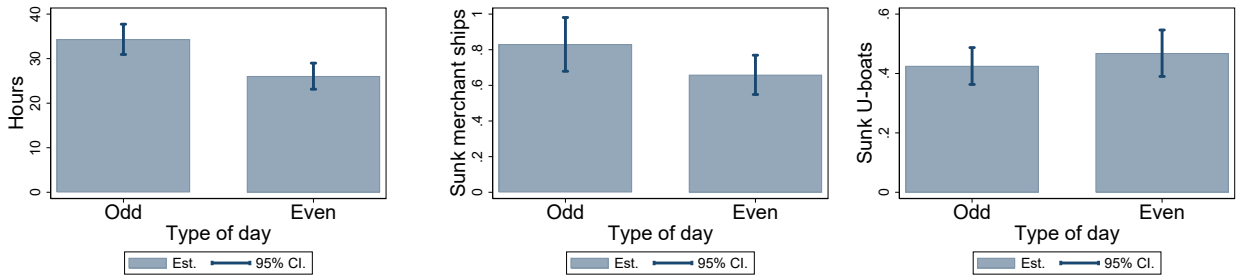
We can relate this back to Jürgen Rohwer (1979)'s exemplary case study. In the early morning hours of October 12, 1941, BP cryptanalysts broke the key from two days earlier, the 10th, an even calendar day. This relatively timely break allowed them to instruct a convoy to reroute at 1 pm on the 14th. The unobserved counterfactual would be the same day but with the key being identified 8 hours later. Said convoy would then have possibly encountered U-boats. The exercise here

[22] Estimates are presented in Appendix Table D1.
[23] Estimates are presented in Appendix Table D3.
[24] Placebo estimates are presented in Appendix Table D4. Note, the point estimate are similar in magnitude to the baseline two-day difference. But to interpret it, one needs to account for the much higher baseline outcome variation in no-Enigma periods. Relative to the mean, I identify an insignificant 6 percent difference in merchant ship losses from odd to even days.

essentially quantifies the effects of such a delay.

However, I do not find a similarly pronounced two-day cycle in the sinking of U-Boats (Figure 6 Panel (c)).[25] One interpretation of this differential pattern—in line with Prediction 1 in Section 3—is that it was a result of deliberate decisions to avoid greater Nazi suspicions. But an alternative explanation is that swift rerouting instructions had immediate benefits while searching and striking U-boats had a longer time lag before realization. Impacts potentially dissipated across odd and even days. In this scenario, the two-day cycle analysis may simply not identify existing effects. To conclude, the evidence suggests that intelligence mattered at least in one dimension, but the design may not be suitable for studying U-boat sinkings.

Figure 6: Two-day cycles in decryption time and conflict outcomes.



(a) Decryption time (b) Sunk merchant ships (c) Sunk U-boats

Notes: Panel (a) shows the average time to identify a daily Enigma key, for both odd and even calendar days. Panel (b) shows the average number of daily merchant ships hit by Nazi U-boats. Panel (c) shows the average number of Nazi U-boats sunk daily. Bars represent robust 95 percent confidence intervals.

5.2 U-Boat-Level Evidence

In this subsection, I try to address previously discussed limitations by focusing on a more granular analysis. Specifically, I investigate how the revelation of specific U-boat locations influenced individual-level outcomes. This allows me to trace out effects over time and along an extensive margin.

[25] Estimates are presented in Appendix Table D3.

Case study. To fix ideas, it is again instructive to begin with a specific case study. Syrett (1999) details the exemplary journey of U-860. The U-boat went on its maiden patrol fairly late in the war, on the 12th of April 1944, heading from Kiel through the Northern Atlantic toward the Far East. The Allies first learned of U-860's existence on the 27th of April, when it was instructed to deliver a series of weather reports. Curiously, these reports were never properly received by the Germans due to radio signal disturbances. Yet, the Allies received them and the radio signals helped to broadly geolocate the vessel. Eventually, on the 6th of May, U-860 was ordered to stop sending weather reports and the Allies had to rely on rough estimates of subsequent positions.

On the 18th of May, U-860 was directed towards the west of India. The Allies read the message and responded. With the intent to intercept the U-boat on its way, escort carrier USS Solomons and four accompanying destroyers left Brazil for the South Atlantic. On June 9th, U-860 broke radio silence, reporting its exact position south of St. Helena in the Atlantic. The message was decrypted a day later. As a result, the Allied task group narrowed down and aircraft began searching. The first sighting was reported on the 15th of June by ensign G.E. Edwards. However, after several rounds of attacks, Edwards was fatally hit by anti-aircraft gunnery. Syrett (1999) conjectures "had [U-860] remained submerged there was the possibility that she might have escaped from the Americans". Yet, Captain Büchel, ordered the U-boat to resurface to give the anti-aircraft gunmen additional practice. After more aircraft were dispatched, rocket fire eventually delivered the *coup de grâce*, sinking U-860.[26]

A few takeaways are worth highlighting. First, messages as simple as weather reports were helpful for the Allies. While they did not necessarily allow for precisely determining a location, they enabled the Allies to learn of a U-boat's existence and subsequent channeling of resources. Secondly, even when a decrypted message revealed a U-boat's position, its fate was not immediately sealed—the Allies often searched for days before locating the vessel. Finally, while this case study is valuable in documenting a precise chain of events, it falls short in constructing counterfactual scenarios.

[26] In the collected and digitized data from the National Archive, I am able to successfully capture the key decrypts: the initial weather reports, instructions to sail toward India, and the fatal position report that led to U-860's sinking.

Empirical Strategy. To identify causal effects empirically, I employ an event-study design, constructing a reasonable control group that serves as a counterfactual. The goal is to estimate the effect of location revelations of specific U-boats on respective victory rates and own survival probability. Two characteristics in my setup differ from canonical event study designs. First, U-boats report locations frequently, meaning they are typically treated multiple times. I therefore use a stacked event study procedure following Rexer (2025). Second, a key outcome, being sunk, is of absorbing nature. Here, I follow the health literature and identify differences in survival probabilities.

I construct the stacked estimation sample as follows. Let h denote a cohort. Each cohort consists of all U-boats treated on day h and a set of control units. Consistent with the historical case studies showing that Allied responses unfolded within a few days, I restrict the cohort sample to a precise event window spanning five days before and five after h. The control units consist of all U-boats that are actively patrolling on day h but were not treated in the five preceding days or the event day itself. I then stack all h-cohort samples and estimate:

$$Y_{ith} = \underbrace{\sum_{\tau \neq -1} \alpha_\tau I^\tau_{ith}}_{\substack{\text{Event} \\ \text{Dummies}}} + \underbrace{\delta_{th}}_{\substack{h\text{-specific time} \\ \text{FE}}} + \underbrace{\gamma_{ih}}_{\substack{h\text{-specific} \\ \text{U-boat FE}}} + \varepsilon_{ith}. \tag{2}$$

Here, the outcome of interest is the number of merchant victories by U-boat i on day t in cohort h. The event study indicators are denoted I^τ_{ith} with τ indexing event time relative to the treatment day. Moreover, I control for h-specific day fixed effects as well as h-specific U-boat fixed effects. Errors are clustered on U-boat level. Under the assumption of parallel trends, the estimated event study coefficients can be interpreted as the causal effect of location decrypts on U-boat victories over merchant vessels. Note that this approach removes 'bad'-controls (already-treated units) which may lead to biased estimates of average treatment effects in staggered treatment designs (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021).

The stacking protocol deviates slightly from the procedure proposed by Cengiz et al. (2019). The latter suggest comparing treated U-boats to a set of control U-boats that had no treatment in the pre- nor in the post-period. Yet, U-boats communicated fairly regularly, *conditional* on surviving.

Put differently, subsequent treatment events are themselves an outcome. Therefore, excluding 'communicating' U-boats will mechanically raise the share of sunk U-boats in the remaining control group. Intuitively, we would be introducing survivorship bias.

Another challenge associated with U-boat survival as outcome is that one can fundamentally not estimate pre-trend coefficients. The intuition is that if a U-boat is treated on day t, it can't have been sunk on any day before. I therefore estimate the following hazard model,

$$Y_{ith} = \sum_{\tau \geq 0} \alpha_\tau I^\tau_{ith} + \gamma_{ih} + \delta_{th} + \varepsilon_{ith}. \tag{3}$$

The outcome Y_{ith} is a dummy equal to unity unless U-boat i was sunk on day t or any day before. The remainder is as before, except that I do not estimate pre-trend coefficients.

To support the validity of the control group, I evaluate balance in pre-period covariates. I follow Imbens and Rubin (2015) and focus on normalized differences.[27] Specifically, I compare the current patrol number, days on current patrol, the number of previous location revelations, messages without geo-information, previously sunk merchant ships, commander experience in days, latitude, and longitude—all measured the day before the cohort treatment day. In Appendix Figure D3, I show that most of the covariate differences fall within Imbens and Rubin (2015)'s 0.25 rule-of-thumb. Treatment units are, however, far more west than control group units and plausibly more exposed to enemy units. To flexibly account for covariate imbalances, I test numerous reweighting schemes.

Results. I begin by discussing the baseline effect of location decrypts on U-boat success rates in sinking merchant vessels. The associated event study coefficients are shown in Figure 7 Panel (a). Following a location revelation U-boat success rates in sinking merchant vessels decline by roughly 0.72 p.p. for at least five days.[28] Given a sample mean of 0.89 p.p. (Table 2), this implies U-boats lose roughly 80 percent of their effectiveness once their positions are decrypted—a substantial decline.

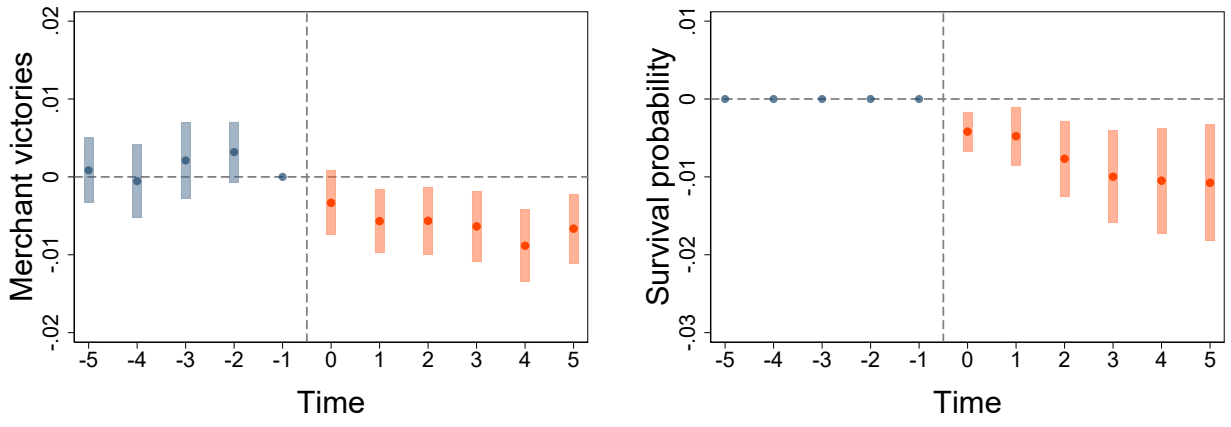
[27] The normalized difference is calculated as $\Delta = \frac{\bar{\mu}_t - \bar{\mu}_c}{\sqrt{(\sigma_t^2 + \sigma_c^2)/2}}$, where $\bar{\mu}_t$ and $\bar{\mu}_c$ are sample means for a given covariate in the control and treatment groups. σ_t^2 and σ_c^2 are the associated sample variances.

[28] The average treatment effect is reported in Appendix Table D5.

A key assumption for the causal interpretation is that, absent a decryption, treated and control units would have followed similar trajectories. Reassuringly, the pre-treatment coefficients are close to zero and show no systematic deviation before the treatment event.[29] This suggests that the parallel trend assumption is at least satisfied in the pre-period.

Next, I turn to the impact of decrypted location messages on U-boat survival. I find that once U-boat positions are revealed, U-boats experience a small but highly significant reduction in survival probability (Panel (b)). After five days, treated U-boats are 1.1 p.p. less likely to survive relative to the control group. The Allies sank only one additional U-boat for every ninety messages with precise geo-information—a seemingly modest decline. Yet, several explanations are plausible: decrypted information may have regularly arrived too late for precise strikes; resource constraints may have limited Allied responses; or attacks on U-boats were simply unsuccessful. I argue that part of the explanation lies in deliberate restraint. To prevent the Germans from suspecting that Enigma codes were compromised, the Allies regularly refrained from acting on decrypted intelligence—a hypothesis I explore later.

Figure 7: Revealing positions: merchant victories and U-boat survival.



(a) Sunk merchant ships

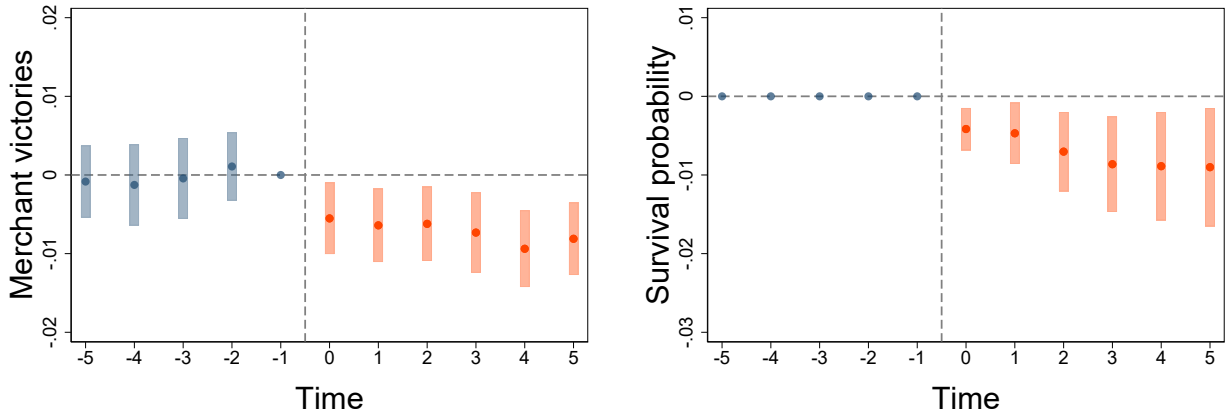
(b) U-boat survival

Notes: Left-hand figure presents event study point estimates for the differences in victories over merchant ships by revealed U-boats versus the clean control U-boats. Right-hand figure presents survival probabilities. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

[29] A formal F-test also fails to reject the null hypothesis that the pre-trend coefficients are jointly zero (p-value: 0.365).

Robustness. These baseline results are robust along several dimensions. A primary concern is the potential endogeneity of sending a location message. For instance, U-boats might report convoy sightings at specific coordinates shortly before engaging in combat. If the U-boat is then destroyed during the engagement, the observed decline in survival could reflect combat risk rather than the effect of decryptions. First note, this mechanism cannot explain the fact that U-boats become far less likely to sink merchant vessels following a location decrypt. Second, to further address this concern, I restrict the analysis to a subset of decrypted messages that do not co-mention merchant convoys. This primarily excludes convoy sightings or reported merchant victories. As shown in Figure 8, the estimated patterns remain similar to the main results.[30] If anything, pre-treatment coefficients move closer to zero, likely because the exclusion removes position-bearing messages that report previously successful strikes on Allied ships.[31]

Figure 8: Revealing positions: messages without co-mentioning "convoy."



(a) Sunk merchant ships

(b) U-boat survival

Notes: Left-hand figure presents event study point estimates for the differences in victories over merchant vessels by revealed U-boats versus the clean control U-boats. Right-hand figure presents survival probabilities. Treatment of interest are decrypts with location information that do not co-mention "convoy." Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Next, I probe robustness against covariate imbalance, applying a battery of reweighting schemes to refine the selection of the control group. This is particularly important because treated U-boats tend to operate further west in the Atlantic (Appendix Figure D3), exposing them to potentially

[30] The average treatment effect is reported in Appendix Table D5.

[31] In Appendix Figure D2, I test further refinements of the treatment definition, excluding messages bearing the following strings: "assist*", "attack*", and "aircraft."

greater risk independent of decryption. Reweighting helps mitigate this geographic confounder while flexibly balancing other relevant pre-treatment characteristics. I use both propensity score weighting as well as entropy balancing (Hainmueller, 2012) on the number of previous patrols, current patrol length, previously decrypted messages, prior victories, commander experience measured in days, latitude and longitude.

First, I compute propensity scores $\hat{p}$ using a probit model. I then generate twenty discrete bins and weight the control units in each bin so that they attain the same sample size as the treatment group. Second, I test robustness using overlap weights (Li, Thomas and Li, 2019). These are calculated as $w_i = 1 - \hat{p}$ for treatment and $w_i = \hat{p}$ for control units. Intuitively, observations with propensity scores close to 0.5 are given more weight while those with extreme values are down-weighted. Finally, I implement entropy balance weights, which directly target covariate moments (Hainmueller, 2012). Appendix Figure D3 visualizes the reductions in normalized differences for the differently weighted groups—all values fall clearly within the 0.25 cutoff range (Imbens and Rubin, 2015). Appendix Figure D4 shows that the baseline event study patterns re-emerge with similar magnitudes in all weighted-samples.[32]

I also assess the robustness of results to alternative outcome definitions. This helps ensure that the main finding is not sensitive to a particular outcome measure or driven by particular distributional properties of the data. First, I re-estimate the baseline regression using the inverse hyperbolic sine of merchant ship victories, which reduces sensitivity to large values. The estimated coefficients closely mirror the baseline pattern (Figure D5 Panel (a)). Second, I broaden the outcome to include victories over both merchant ships and battleships. Results remain robust, yet the effect size increases (Panel (b)).[33] Finally, I consider alternative U-boat outcomes, including the number of merchant sailors lost (Panel (c)) and the tonnage of ships sunk (Panel (d)). In both cases, the results closely track the baseline estimates.

A further robustness concern relates to potential spillovers across nearby U-boats, which could violate the Stable Unit Treatment Value Assumption (SUTVA). If decrypt-induced operations affected not only the directly revealed U-boat but also others operating nearby, which is reasonable

[32]The average treatment effects are reported in Appendix Table D5.
[33]The average treatment effects are reported in Appendix Table D5.

given the geographic nature of the treatment, then control units in close proximity might experience indirect treatment effects. To assess potential confounding, I restrict the control group to U-boats operating at least 200 km, and then 500 km, away from any treated U-boat on the day before treatment. The resulting estimates remain robust to these control group refinements (Appendix Figure D6). While the estimated effect on ships saved is quantitatively similar, I observe somewhat larger declines in survival probability (from -1.08 p.p. to -1.44 p.p.) when nearby U-boats are removed from the control group. This pattern is consistent with localized treatment spillovers biasing baseline effects toward zero.

Finally, I test the sensitivity of results to particular time periods. I re-estimate baseline difference-in-differences effects on subsamples while iteratively removing entire year-months. The resulting point estimates show little variation, suggesting that effects are not driven by any particular time period (Appendix Figure D7).

5.3 Evidence on Heterogeneity and Mechanisms

The richness of the data allows me to study different dimensions of heterogeneity. This is useful because it allows for testing auxiliary predictions of the strategic restraint mechanism. I focus on three U-boat dimensions: commander ability, time during the war, and identity of operational control. I conclude by examining heterogeneity in Allied shipping losses.

U-boat capacity. First, I explore heterogeneity in commander ability. The idea is that if the Allies wanted to sink some U-boats, but not all, they should eliminate those that pose the greatest danger—U-boats with skilled commanders and a successful record of sinking merchant ships. A condition for such precise targeting is sophisticated tracking of individual level information. The historical literature suggests that the Allies were indeed doing so. For instance, Syrett (1998, p. xxiv) documents how the Allies computed statistics on commander experience and Kohnen (2019, p. 259-260) discusses an example of how the kill history for a commander was established: U-188, lead by Siegfried Lüdden, carried specific insignia and logos on its hull. These were identified in interviews with survivors of sunk Allied ships, allowing intelligence officers to tie ship losses to this particular U-boat.

While I am unaware of historical references prescribing selective targeting based on U-boat commander capacity, targeting based on another dimension of value has received attention. A handful of submarines served solely the purpose of refueling other U-boats on patrol. These U-tankers were important for prolonging ongoing patrols—thereby having high value along a different margin. Late military historian Kahn (1991, p. 267) describes that it was for this reason that U-tankers were the first units to be actively targeted with the help of Enigma decrypts.

I extend this idea to a different type of value, commander capacity. To the best of my knowledge, this dimension has hitherto remained unexplored. But it comes with an empirical advantage: there is large variation across all U-boats. To measure capacity, I estimate commander fixed effects (FE) using victory rates over merchant vessels, arguing that these capture variation in the inherent quality of commanders.[34] To improve precision, I apply empirical Bayes shrinkage to these estimates (Walters, 2024).[35] I then split the data into above and below-median commander subsamples and estimate coefficients separately.

The estimated coefficients are shown in Figure 9. I find that high-FE commanders suffer survival declines of about 1.9 p.p. after five days with virtually no effect accruing to low-FE commanders. This is consistent with the idea that the Allies predominantly used decrypts to remove high-value targets, sparing lower-value targets.[36]

Time. Next, I examine how the effects of decrypts vary over time, which speaks directly to Prediction 2. The theoretical model implies that the strategic value of keeping the Enigma breach secret should decline as the war draws to a close. In the later stages of the conflict, the Allies had fewer incentives to preserve secrecy and stronger incentives to act quickly on intelligence. Commander Kenneth Knowles (1977) provides anecdotal support for this shift: "We skated on some

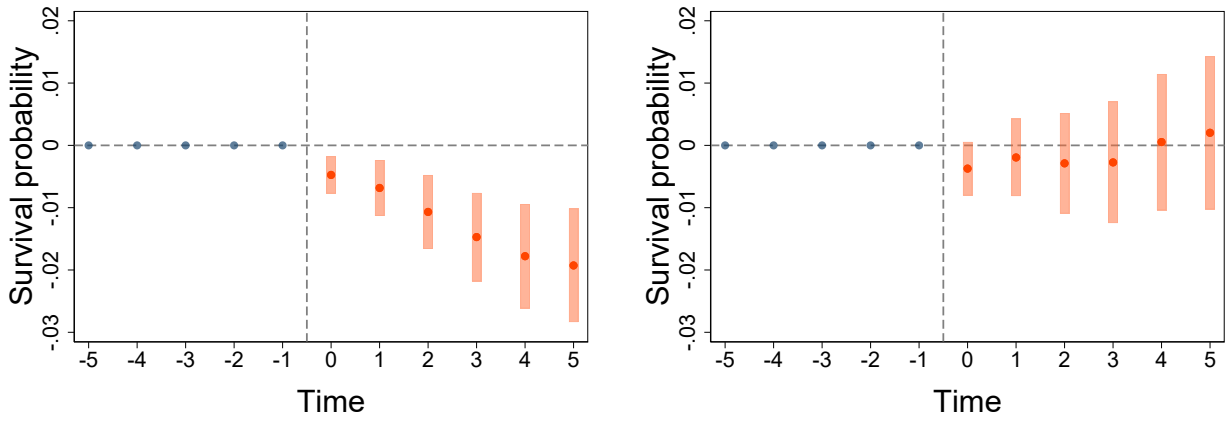
[34] Commander FE are estimated as $Victories_{it} = \alpha_i + \gamma_t + \varepsilon_{it}$, where α_i captures commander-level fixed effects and γ_t flexibly accounts for year-by-month fixed effects.

[35] The precise protocol is as follows.

1. Estimate raw fixed effects ($\hat{\alpha}_i$) and associated standard errors (s_i).
2. Estimate hyperparameters of prior distribution $\hat{\mu} = \frac{1}{N}\sum_{i=1}^{N} \hat{\alpha}_i$ and $\hat{\sigma}^2 = \frac{1}{N}\sum_{i=1}^{N} (\hat{\alpha}_i - \hat{\mu})^2 - (s_i)^2$.
3. Compute shrinkage weights $\lambda_i = \hat{\sigma}^2/(\hat{\sigma}^2 + s_i^2)$.
4. Shrink raw estimates $\alpha_i^* = \lambda_i \cdot \hat{\alpha}_i + (1 - \lambda_i) \cdot \hat{\mu}$.

[36] In Appendix Figure D8, I show that the same pattern emerges using the raw fixed effects split.

Figure 9: Revealing positions: U-boat survival by captain quality.



(a) Above-median fixed effects

(b) Below-median fixed effects

Notes: Figure presents event study point estimates for the differences in survival probabilities by revealed U-boats versus the clean control U-boats. The left-hand side shows estimates for above-median commanders in terms of merchant victory fixed effects after empirical Bayes shrinkage. The right-hand side shows estimates for below-median commanders. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

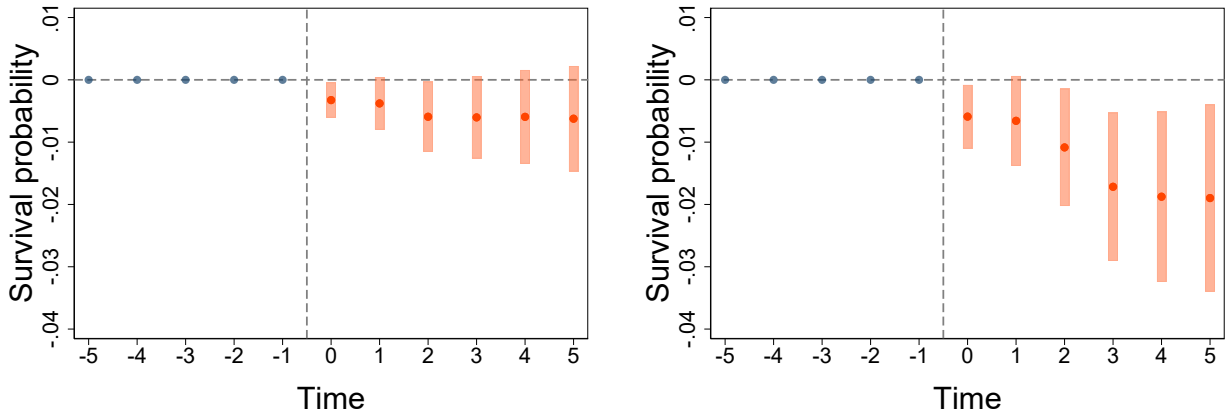
pretty thin ice in one instance later in the war when it became imperative that we gain decisive victory as soon as possible" (p. 14). The remark refers to cases where several U-boats were sunk despite the absence of high-quality alternative intelligence sources, illustrating a more aggressive use of decrypts late in the war.

To investigate the empirical relevance of this channel, I split my sample period into two halves, 1942/43 and 1944/45, and estimate hazard rates separately. The coefficients are shown in Figure 10. Consistent with the model, I find that decrypts predict relatively small reductions in survival probability earlier in the war, but larger reductions in the final two years. Again, this is consistent with the Allies rationally varying intelligence utilization.

This temporal pattern does not appear to reflect shifts in perceived Allied winning probability but rather a shorter remaining window to exploit intelligence. Appendix Figure D9 shows that, following the Battle of Stalingrad, sterling's black-market exchange rate against the U.S. dollar—a proxy for Allied winning probability (Einzig, 1970, p. 257)—remained fairly stable throughout my estimation period. I am, however, mindful that technological improvements—such as advances in radar and increasing air coverage—also enhanced the Allies' ability to act on location information

toward the end of the war. While these improvements would also have affected the control group, I cannot disentangle their increasing influence from that of changing intelligence utilization.

Figure 10: Revealing positions: U-boat survival earlier and later in the war.



(a) 1942-1943

(b) 1944-1945

Notes: Figure presents event study point estimates for the differences in survival probabilities by revealed U-boats versus the clean control U-boats. The left-hand side shows estimates for 1942-1943. The right-hand side shows estimates for 1944-1945. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Operational Control. Finally, I exploit variation across different Allied partners in line with Prediction 3. One reason to expect differential effects is that the loss of Enigma intelligence loomed larger for the British than the American Allies.[37] In the data, the effect on U-boat survival should therefore be smaller in British naval zones. However, there may be other reasons outweighing any observable differences. Due to closer proximity to land-based aircraft, the British were possibly more effective in swiftly targeting U-boats.

I split the sample into American versus British designated areas. I proceed as follows. Generally, the US Navy was responsible for the Central and South Atlantic (Kohnen, 1999, p.119). Consistent with Barlow (2008), I code regions South of Aruba as American responsibility. However, many U-boats in the North Atlantic were also sunk by American forces. I therefore split water regions at longitude 6.31° West. I choose this longitude because it marks the Easternmost position of a

[37] US Navy Captain Knowles (1977), for instance, opined: "[W]e Americans viewed the U-boat conflict, at least at our entry, more as a challenge than as a struggle for survival." (p. 13)

U-boat sunk by American forces.[38] Conveniently, this designation splits the data set into two similarly sized samples for estimation.

The results of the split-sample regressions are shown in Figure 11. The point estimates suggest that decrypts lead to only a small, statistically insignificant, reduction in survival for U-boats in the British-designated areas. Most of the variation in the main effect is driven by American forces. This suggests that the British indeed exerted greater restraint in using Enigma intelligence compared to the Americans. Note that the same event study, but with merchant victories as outcome, is instead highly symmetrical (Appendix Figure D10). This rules out that the differences in survival rates are due to different information sets.

Written correspondence between American and British military leadership support the notion that security concerns were the main reason for these differences (Kohnen, 1999, p. 128-130). This is well-exemplified by another quote from U.S. Navy Commander Kenneth Knowles. Knowles said of his British counterpart, Rodger Winn, a senior official in the OIC:

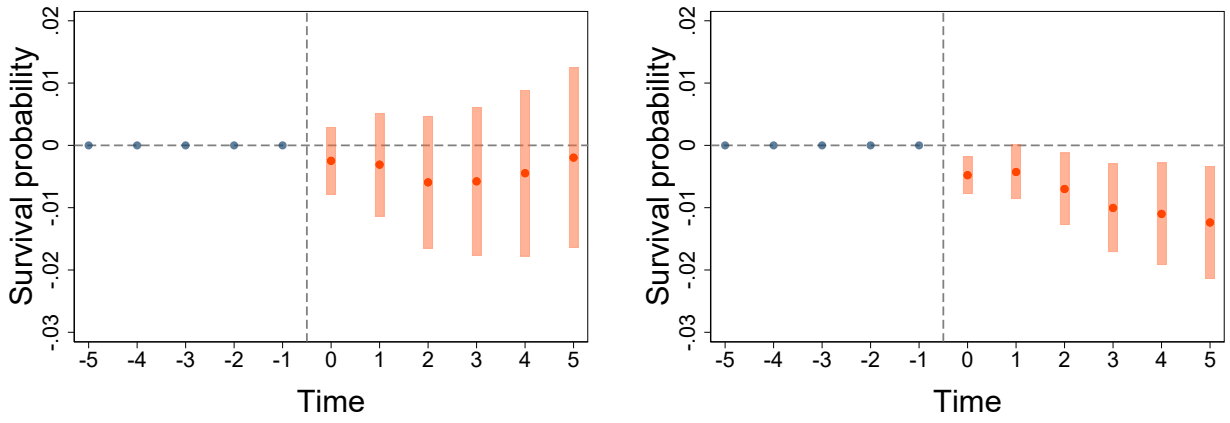
> "Ro[d]ger had the feel of the British, naturally, of protecting ULTRA [Enigma intelligence] at all costs. So they were very cautious in utilizing ULTRA. [...] Whereas, over in my area, being younger at the game and also being somewhat aggressive we were using ULTRA more aggressively. There's quite a difference in philosophy here." (as cited in Kohnen (2019, p. 263))

Types of ships. I also explore potential heterogeneity in whether decrypts affected Allied shipping losses differentially. I previously argued, that strategic restraint is less binding in this more noisy outcome dimension. We would therefore expect small quantitative differences or absence of heterogeneity.

To test this hypothesis, I estimate heterogeneity in shipping losses by ship size and cargo type (Appendix Table D7). I split the sample into above- and below-median tonnage, and further isolate ships carrying only ballast (i.e. material used to stabilize an otherwise empty vessel). The

[38] See, *"U-boats Sunk by U.S. Forces with Aid of Radio Intelligence"* in Appendix I of *"OP-20-GI, Memoranda to COMINCH F21, on German U-Boat Activities, October 1943-May 1945."*, Record Group 457, National Archives, College Park, Maryland

Figure 11: Revealing positions: U-boat survival in different Atlantic zones.



(a) British waters

(b) American waters

Notes: Figure presents event study point estimates for the differences in survival probabilities by revealed U-boats versus control U-boats. The left-hand side shows the effect on U-boats in British-designated waters. The right-hand side shows the effect on U-boats in American-designated waters. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

estimates reveal that the relative effect sizes are remarkably similar across all categories. When positions are revealed, Allied shipping losses decline by roughly 80-95 percent relative to the estimation sample mean, regardless of ship type. The absence of systematic heterogeneity provides further evidence that decrypt-based rerouting decisions were applied broadly rather than selectively.

Discussion. I document heterogeneity in intelligence utilization against U-boats along different dimensions. I interpret these results as consistent with a mechanism of strategic restraint. However, I recognize that some of the variation I uncover may stem from alternative mechanisms.

In particular, resource constraints could also explain some of these patterns. Under limited availability of anti-submarine units, we would equally expect the Allies to concentrate their efforts on targeting high-value U-boats. Indeed, as resource availability improved over the course of the war, it could account for some of the increasing impact of location decrypts on U-boat losses. However, resource availability alone does not fully explain the geographic differences I uncover. Specifically, British land-based aircraft, due to their closer proximity, could have been a much more effective tool against U-boats. Yet, the empirical analysis shows minimal effects—contrary to what one

would expect if resource constraints were primary drivers of heterogeneity.

In previous paragraphs, I have already drawn on several anecdotes to support the argument that strategic restraint was top of mind among Allied leadership. To give further concrete support for this argument, I turn to a final piece of historical evidence focusing on a different context.

Specifically, I draw on a report by Group Captain R.H. Humphreys, a senior rank official at Bletchley Park, dating back to October 1945.[39] The report discusses disruptions to Nazi supply lines in the Mediterranean theater and reinforces several key points. First, security of the intelligence source was of utmost importance, also in this context. Humphreys states that "offensive action was NOT taken against any such shipping targets UNLESS there was clearly a second source" (p. 2), such as air reconnaissance.

Second, the report also addresses the strategic prioritization of different targets. In fact, "the information supplied permitted the establishment of an order of priority for the attack of convoys of greater or lesser importance" (p. 2). Again, this aligns closely with the heterogeneity I uncover empirically: Enigma messages primarily affected the survival probability of high-value U-boats.

Third, Humphreys alludes to differences in intelligence exploitation over time. He contents, that utilization "suffer[ed] from over-timidity in the beginning" but, interestingly, does not view missed opportunities with remorse: "because there was insufficient experience prudence could hardly be exaggerated" (p. 17).

To conclude, the dilemma of wishing to exploit Enigma intelligence while concealing its source was a persistent concern among decision-makers throughout the war. The heterogeneities observed in the data are consistent with this mechanism, as are numerous pieces of anecdotal evidence.

5.4 The Value of Content

While many decrypted messages included explicit geographic information, others did not: situation reports, fuel updates, or even congratulatory greetings. Historians have suggested that even

[39] "The Use of 'ULTRA' in the Mediterranean and Northwest African Theatres of War". P.R.O. AIR 40/2323, National Archives, London, Kew.

such messages could offer strategic value, since radio signal triangulation allowed the Allies to infer rough locations from transmission bearings. Yet it remains unclear how much of value came from the actual content of decrypted messages versus direction-finding alone. In this subsection, I briefly shed light on this question: I examine whether decrypts without geoinformation had measurable operational effects on U-boat performance.

To do so, I conduct an exercise analogous to the baseline analysis. I identify all decrypted U-boat messages that lack explicit location references and treat their decryption as the event of interest. To ensure clean identification, I restrict the sample to U-boats that had not sent or received any coordinate-bearing message on the event day or in the preceding five days. This design isolates potential effects of non-location messages from those driven by precise geoinformation.

Figure 12 presents the results. Panel (a) shows the estimated effect on U-boat victory rates over Allied merchant ships. Unlike the substantial and persistent declines following location decrypts, the coefficients here are close to zero and do not indicate substantial differences in U-boat effectiveness. Panel (b) examines survival probabilities. While there is a modest decline on the exact day of message decryption, the effect is short-lived and quickly dissipates therafter.

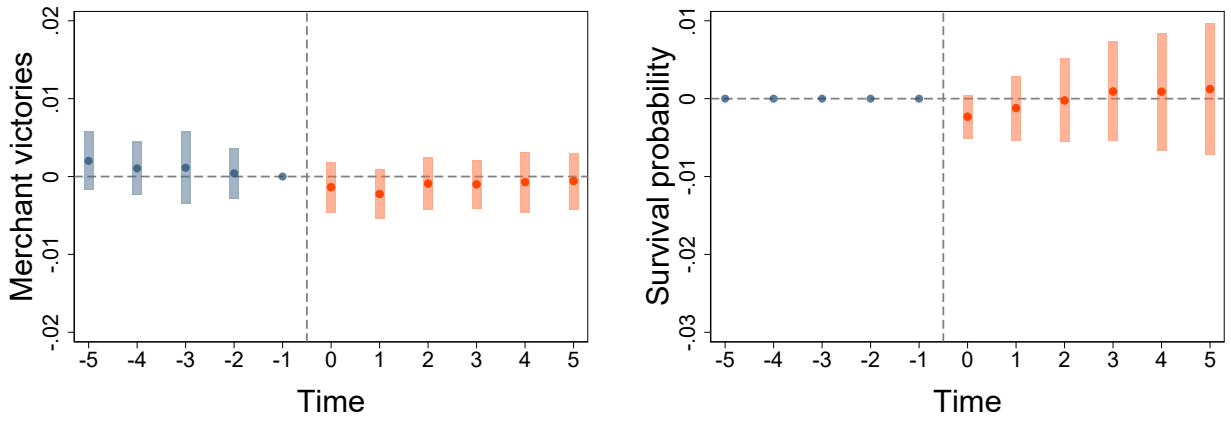
Taken together, these findings suggest that radio messages without explicit geoinformation did not materially impair U-boat operations—at least locally. However, these messages may still have provided strategic value, such as improved estimates over the total number of patrolling U-boats and their broader geographic density.

6 Aggregate Impact

In this section, I turn to a final exercise. I ask, what was the aggregate impact of Enigma decrypts on the *Battle of the Atlantic*? As this is a very broad question, I limit myself to two channels: (1) saving ships through rerouting and (2) the preventive sinking of U-boats to avoid future ship losses.

To estimate the first effect is straightforward. I combine the reduced form estimate from the U-boat efficiency loss (0.72 p.p.), the effect duration (6 days), and the number of location revelations

Figure 12: Messages without location: merchant victories and U-boat survival.



(a) Sunk merchant ships

(b) U-boat survival

Notes: Left-hand figure presents event study point estimates for the differences in victories over merchant vessels by U-boats with placebo messages versus the control U-boats without such a message. Right-hand figure presents survival probabilities. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

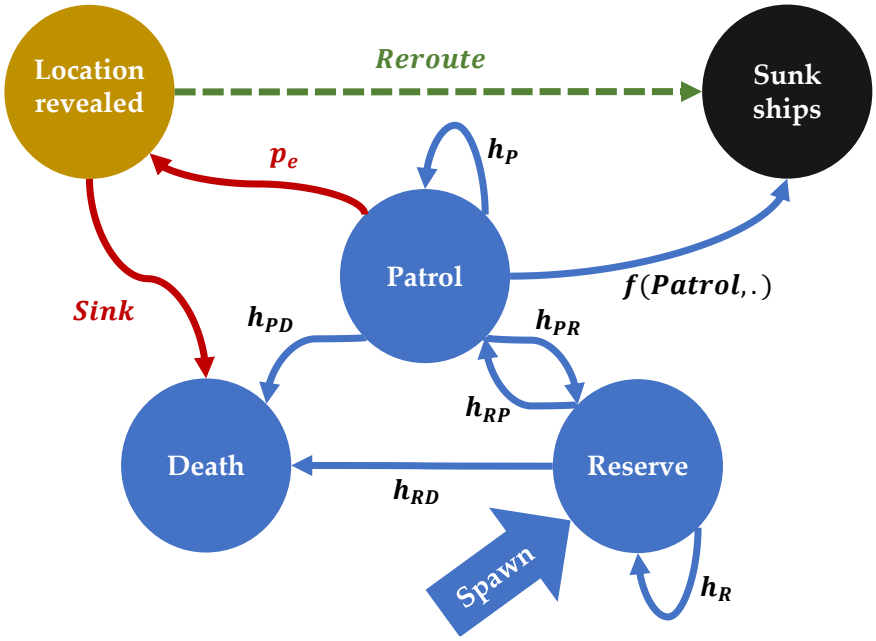
(7443). This implies that roughly 322 ships were rerouted and saved directly from December 1942 until the end of the war.

Gauging the second effect, however, is more complex. U-boats were sunk for various reasons at different times and it is unclear how long U-boats would have survived in a counterfactual world without location revelations. To address this challenge, I set up a simple simulation framework characterizing different U-boat states and flows between those states to simulate counterfactual distributions of patrolling U-boats.

The setup is as follows. New U-boats are regularly built. Once built, they are either off-duty in *reserve* (e.g., for training or repairing purposes) or they are actively on *patrol*. In both states, U-boats can *sink*. U-boats on reserve were often bombed while stationed at ports while those on patrol were sunk e.g. in combat or by accident. Flows among the states are characterized by transition rates. The key metric of interest is the number of U-boats on patrol each day, which eventually determines the number of sunk merchant ships. Figure 13 presents an overview.

To quantify the effect of saved merchant ships in the future, I simulate counterfactual distributions of the number of patrolling U-boats where I remove the added hazard from Enigma decrypts.

Figure 13: Simulation structure.



Notes: This graph characterizes the U-boat states and transition rates h.

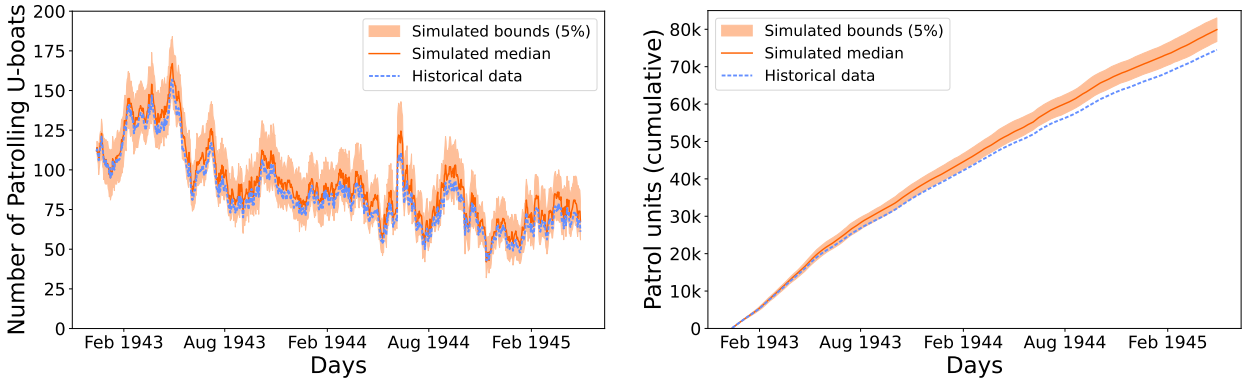
From December 1942 until the end of the war, U-boats had a mean hazard rate of sinking of 0.68 p.p. every day on patrol. In the previous section, I estimated that location revelations increased the hazard rate by 1.1 p.p.[40] and that U-boats reveal their location with a 10 percent probability. Assuming a simple additive hazard rate, this implies that in a world without Enigma decrypts, U-boats would experience an average hazard rate of $0.68 - 1.1 \times 0.1 = 0.57$.

To simulate counterfactuals, I take the empirical distribution of U-boat states in December 1942 as well as the empirical production and transition rates over the subsequent years. I then remove the added hazard rate to match the estimate in the reduced-form exercise and simulate one hundred counterfactual distributions. Figure 14 Panel (a) shows the historical number of patrolling units alongside the median and five percent bounds of the simulated counterfactuals. Interestingly, removing the added hazard rate seems to have only a small effect on the aggregate number of patrolling units. The reason is that the baseline production rate of new U-boats and the baseline hazard rates of sinking/going back to reserve are far larger than the added Enigma hazard.

[40] While the 1.1 p.p. in the reduced form exercise is the cumulative difference after five days, here I collapse it for simplicity to one day.

On average, roughly 6 more U-boats are on patrol every day. However, this difference becomes quantitatively meaningful when cumulated over the relevant sample period, implying about 5200 more unit-on-patrol days in the median scenario until the end of the war (Figure 14 Panel (b)).

Figure 14: Patrolling U-boats: Empirical versus simulated distribution.



(a) Number of U-boats on patrol

(b) Cumulative U-boat-patrol days

Notes: This figure shows the results of counterfactual simulations, where I remove the estimated, added hazard from Enigma decrypts. The dashed lines indicate the historical time-series data, whereas the solid lines show the median of 100 counterfactual simulations. Light backgrounds indicate the 5 and 95 percentile bounds. The left-hand side depicts the number of patrolling U-boats per day from December 1942 - May 1945. The right-hand side shows the cumulative number of U-boats-on-patrol days.

How does this increase in unit-on-patrol days relate to merchant ship losses? I estimate a simple linear model linking the daily number of U-boats on patrols to sunk merchant ships. In the preferred specification with month-by-year and day fixed effects, one more U-boat on patrol is associated with 1.9 p.p. more merchant ships sunk per day (Table D8 Column 3). Taken together, this implies that had there been no sinkings of U-boats through Enigma decrypts, we would have expected an additional loss of 99 merchant ships.

Combining the effect of both channels, approximately 421 ships were saved, while the actual number of merchant ship losses was 601 over the relevant sample period (December 1942 until May 1945). This implies that Enigma decrypts lowered expected merchant losses by roughly 40 percent. Additionally, in this period the mean number of lives lost per ship was roughly 16. Assuming a similar rate for ships sunk in the counterfactual, I estimate that close to 6700 lives were saved through Enigma decrypts in the Atlantic.

Limitations. While the simulation, as is, provides valuable insights into the aggregate impact of Enigma decrypts, it is subject to some limitations. For instance, the framework does not explicitly account for the role of U-tankers, U-boats designed to refuel other U-boats on patrol. As discussed before, U-tankers were subject to early targeting by the Allies, because they were crucial for prolonging patrols. Kahn (1991, p. 265) estimates that with two refuels, average patrol length could essentially be doubled. In the counterfactual environment, the Allies would likely not have struck as many refuel U-boats. Transition rates from patrol to reserve would have been lower, increasing the aggregate number of patrolling units even more. Omitting this channel, the simulation is likely to understate the true impact of Enigma intelligence.

Another key limitation is, that I do not observe aggregate merchant ship stocks and do not include it in the model. This may also introduce bias in estimating long-term merchant losses, albeit in the opposite direction. If more ships are sunk early in the sample period, fewer vessels remain available for future voyages, naturally reducing the probability of U-boats encountering and sinking merchant ships in later periods. Not accounting for this dynamic, the simulation may overstate the impact of Enigma intelligence.

However, several factors help mitigate this concern. First, the share of ships lost per voyage was generally very low. Among convoy voyages, the risk was just 0.8 p.p. across the entire war,[41] meaning that even if more ships were lost early, the overall impact on shipping stocks and long-term losses would have been relatively small. Second, greater losses would have likely prompted the Allies to ramp up ship production. Hundreds of shipping contracts were canceled before the war ended (Williams, 2014, p.17 & 46), suggesting that replacement capacity was available. Finally, I also do not uncover a significant nor quantitatively meaningful relationship between the number of voyaging ships and the number of sunk ships, once time trends are properly controlled for (Appendix Table D8 Column 3).

To conclude, the simulation does not account for all forces at play. The quantification exercise relies on the assumption that omitted factors either counterbalance one another or have limited quantitative significance. Given the arguments above, this assumption appears reasonable.

[41] 0.62 p.p. in periods of Enigma intelligence and 0.95 p.p. in periods without.

Validation. Relying on a different approach, I provide a simple validation exercise. The details are in Appendix D.1. To probe the validity of the aggregate estimate, I use a simple difference-in-differences design comparing higher-level outcomes between different Axis powers. Specifically, I focus on four months before and after December 1942, when the Allies began reading Nazi U-boat ciphers again, but no such change occurred with respect to Italian and Japanese submarines.

Compared to this control group, I find that in the subsequent months, German submarines sank roughly 0.8 fewer merchant ships per day (Appendix Table D10). In relative terms, this corresponds to a reduction of roughly 32 percent, which broadly aligns in magnitude with the simulation result.

Counterfactuals. The simulation allows us to perform counterfactual experiments. First, I consider how many more ships could have potentially been saved had the Allies struck ships with the same efficiency as in 1944/45, already in earlier periods. In this scenario, I find that about 80 more ships could have been saved. Second, what would have been counterfactual outcomes had all U-boats been sunk to the same extent as the above-median capacity sample? Since effect sizes mirror the 1944/45- sample, this scenario also implies about 80 more surviving ships. This suggests, that while there were some untapped gains, Enigma intelligence was already leveraged quite effectively.

Costs and Benefits. Next, I turn to a brief economic assessment. I focus on three objects, cost of intelligence activities, merchant ship and U-boat construction. For present-day evaluations I deflate using the CPI.[42]

I begin by considering the cost of decryption activities. As with many other records, financial documents from Bletchley Park have only partly survived. Smith (2021) has evaluated key expenditure items covering buildings, salaries, and costs of decryption machines. He concludes that the total tally amounts to at least £12 million, or $50 million ($1.1 billion today). While this represents a lower bound (e.g. by omitting American expenditures), total cost appears to be significantly

[42]Specifically, I use the Minneapolis Fed inflation calculator from 1941-2024 https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator. For currency conversion, I rely on the FED Report *Banking and Monetary Statistics, 1914 - 1941* available at https://fraser.stlouisfed.org/title/banking-monetary-statistics-1914-1941-38/part-i-6408.

smaller than what was spent on the Manhattan Project, a staggering $2 billion ($42.7 billion today).

What were the economic gains? Consider that Enigma intelligence saved 421 merchant ships alone from December 1942 onward. A standard ship type to replace losses was the *Liberty*.[43] Average production costs are well documented, equalling roughly $1.8 million in the 1940s (Williams, 2014, p. 31) with a present value of $38 million. This implies Enigma prevented total shipbuilding cost of about $16 *billion*.

But this wasn't the only economic benefit. The continuous destruction of U-boats tied Nazi resources. Again, production cost data help us quantify economic losses. A standard submarine (type VII) cost roughly $1.9 million (Gröner, 1990, p. 44). Hence, the damage imposed on the Germans by the destruction of 80 U-boats through decrypts amounts to $3 billion in lost value.

Taken together, even when considering only the benefits in one specific theater of war: the return on investment from Enigma intelligence was significant.

6.1 Absence of Learning

The aggregate benefits of intelligence were substantial, both in terms of ships saved and economic gains. This raises a fundamental question: why did the Nazis never learn nor realize that communication channels were compromised?

Several factors help explain this failure. As documented throughout this paper, the Allies were highly sophisticated in how they leveraged intelligence. As mentioned in Section 2, they also engaged in deceptive activities. They publicly credited other information sources, such as Air Reconnaissance, for successes in the Atlantic. This reinforced German misconceptions and masked the role of codebreaking. Nevertheless, suspicions did arise on the German side. Mulligan (1985) and Ratcliff (1999) provide in-depth discussions. The German military leadership was aware that codebreaking was technically feasible, but believed it would be too time-consuming to yield operationally useful results. They underestimated both Allied analytical capabilities and the possibility

[43] For the curious reader, Liberty ship production has sparked its own small literature within economics. See Rapping (1965), Thompson (2001) and Thornton and Thompson (2001).

of sustained codebreaking success.

Several internal investigations were launched—in part because of "unexplained losses" (Ratcliff, 1999). Yet all investigations concluded that Enigma codes remained secure. This judgment was shaped by flawed reasoning. German analysts, for instance, noted that decrypted Allied communications only referenced approximate U-boat positions, not precise ones, leading them to believe that radio direction finding—rather than deciphered messages—was the primary intelligence source. Additionally, after an Enigma upgrade in February 1942, the Germans observed no immediate shift in military outcomes, which falsely reassured them of the system's integrity (Ratcliff, 1999).

Beyond these misjudgments, deeper institutional frictions likely played a role. We can liken this to Wintrobe's (1998) "dictator's dilemma," where authoritarian leaders, by creating an environment of fear and control, end up distorting the flow of accurate information. In such systems, subordinates are incentivized to provide optimistic reports rather than hard truths. Some historical assessments permit such an interpretation of the German security blunder. Syrett (1999), for example, conjectures some military officials "perhaps sens[ed] that the Allies were obtaining information from their radio communications"—but this intuition never translated into effective policy reform.

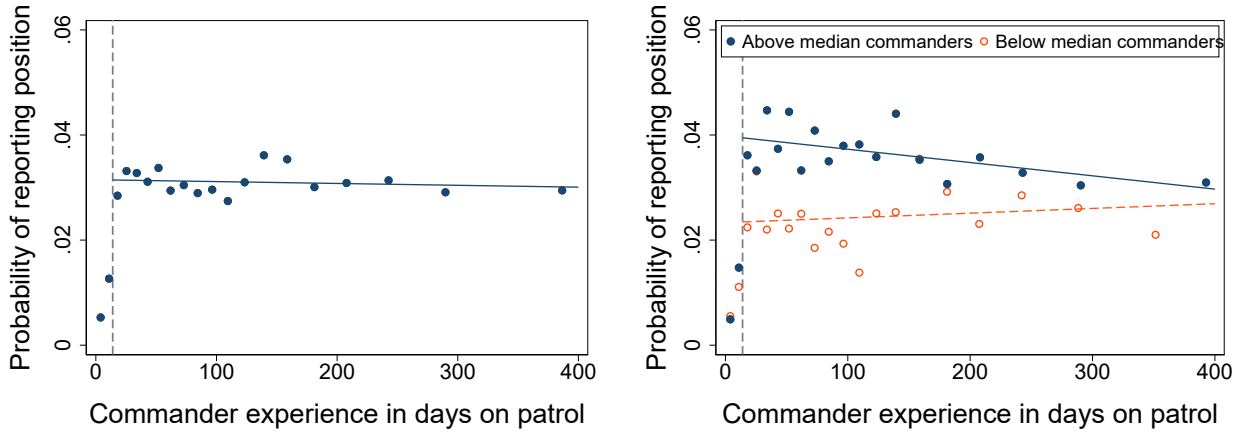
I briefly explore the merits of this hypothesis, as a final exercise. If individual commanders gradually realized that their communications were insecure, we would expect a decreasing tendency to report their position as their patrol experience increased. Figure 15 plots the probability of position decrypts along commanders' patrol experience, measured in days.[44]

Panel (a) shows that after the initial two weeks—typically spent departing home ports—the likelihood of such messages remains relatively constant. However, this average masks important underlying heterogeneity. In Panel (b), I split the data by commander capacity. Among lower-capacity commanders, the frequency of position reports remains unchanged over time. In contrast, above-median commanders appear to grow more cautious. Early in their patrol careers, these commanders report positions with a daily probability of about four percent; after 300 days,

[44]I focus only on messages with position information that were sent from, and not to, U-boats/commanders.

this probability falls to roughly three percent. This asymmetry essentially mirrors the differential impact of decryptions on U-boat vulnerability. While only suggestive, the pattern is consistent with the notion that some commanders grew increasingly wary of Enigma's security. This, in turn, suggests that a different organizational structure or military culture might have been better equipped to detect the Enigma compromise.

Figure 15: Position messages over commander experience.



(a) All commanders

(b) Split by capacity

Notes: Binscatter plots of the daily probability of a position decrypt against commander experience as measured in days on patrol. Panel (a) bins data only by commander experience. Panel (b) is further split in above and below-median fixed effect commanders. Linear relationships are fit on experience levels above at least two weeks, indicated by the gray dashed lines—the first few days are typically spent en route towards a first patrol position with little communication. Coefficients are reported in Appendix Table D9. Data based on the U-boat panel December 1942 to May 1945.

7 Conclusion

This paper studies the role of military intelligence in conflict, focusing on the Battle of the Atlantic during World War II.

By leveraging newly digitized data on U-boat communications coupled with information on merchant vessels, I provide evidence that decrypted Enigma messages were crucial in reducing Allied shipping losses. The findings suggest that intelligence was primarily used to reroute merchant ships and, in parts, to target U-boats. This aligns with the notion of a strategic trade-off in preserving secrecy to maintain long-term informational advantages—an idea that I formalize through

an asymmetric information model. Numerous pieces of anecdotal evidence and distinct heterogeneities in the data support this interpretation.

Through a combination of reduced-form analyses and a semi-structural simulation framework, I estimate that Enigma intelligence helped prevent 421 merchant ship losses from December 1942 until the end of the war—a 40 percent reduction in expected losses. These gains translated into significant economic benefits. I estimate shipbuilding cost savings of about $16 billion in present-day valuation, with damages to Nazi U-boats worth $3 billion. Additionally, Enigma intelligence prevented the loss of approximately 6,700 seamen's lives. Counterfactual exercises indicate that even more gains may have been possible, but they also highlight that the Allies exploited intelligence already extensively.

Finally, the analyses here do not address one important aspect: more efficient supply chains may have ultimately affected the length of the war. This presents itself as a promising avenue for future research.

References

Adena, Maja, Ruben Enikolopov, Maria Petrova, and Hans-Joachim Voth. 2021. "Bombs, Broadcasts and Resistance: Allied Intervention and Domestic Opposition to the Nazi Regime during World War II." *Available at SSRN 3661643*. ↩ 6

Ager, Philipp, Leonardo Bursztyn, Lukas Leucht, and Hans-Joachim Voth. 2022. "Killer Incentives: Rivalry, Performance and Risk-Taking Among German Fighter Pilots, 1939–45." *Review of Economic Studies*, 89(5): 2257–2292. ↩ 6

Axelrod, Robert. 1979. "The Rational Timing of Surprise." *World Politics*, 31(2): 228–246. ↩ 10

Barlow, Jeffrey G. 2008. "The Navy's Atlantic War Learning Curve." *Naval History*, 22(3): 22. ↩ 32

Batey, Mavis. 2011. "Breaking Italian Naval Enigma." In *The Bletchley Park Codebreakers: How Ultra Shortened the War and Led to the Birth of the Computer*. , ed. Ralph Erskine and Michael Smith. Biteback Publishing. ↩ 9

Beesly, Patrick. 1977. *Very Special Intelligence.* Greenhill Books (2000). ↩ 2, 7, 8, 9, and 15

Beesly, Patrick. 1990. "Convoy PQ 17: A Study of Intelligence and Decision-Making." *Intelligence and National Security*, 5(2): 292–322. ↩ 13

Bennett, Ralph. 1996. "Intelligence and Strategy: Some Observations on the War in the Mediterranean 1941–45." In *Intelligence Investigations: How Ultra Changed History*. Chapter 5. Frank Cass Co. Ltd. ↩ 10

Budiansky, Stephen. 2000. *Battle of Wits.* Simon and Schuster. ↩ 7, 15, 21, 52, and 84

Caselli, Francesco, Massimo Morelli, and Dominic Rohner. 2015. "The Geography of Interstate Resource Wars." *The Quarterly Journal of Economics*, 130(1): 267–315. ↩ 1 and 5

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-Wage Jobs." *The Quarterly Journal of Economics*, 134(3): 1405–1454. ↩ 24

Chadwick, John. 2011. "A Biographical Fragment: 1942–5." In *The Bletchley Park Codebreakers: How Ultra Shortened the War and Led to the Birth of the Computer*. , ed. Ralph Erskine and Michael Smith. Biteback Publishing. ↩ 84

Churchill, Winston. 1952. *The Second World War. Closing the Ring*. Vol. 5, Cassell. ↩ 8

Conconi, Paola, Nicolas Sahuguet, and Maurizio Zanardi. 2014. "Democratic Peace and Electoral Accountability." *Journal of the European Economic Association*, 12(4): 997–1028. ↩ 5

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review*, 110(9): 2964–2996. ↩ 24

Dönitz, Karl. 1958. *Memoirs Ten Years and Twenty Days.* ↩ 10

Eichengreen, Barry, Massimo Ferrari Minesso, Arnaud Mehl, Isabel Vansteenkiste, and Roger Vicquéry. 2024. "Sanctions and the exchange rate in time." *Economic Policy*, 39(118): 323–354. ↩ 77

Einzig, Paul. 1970. *The History of Foreign Exchange.* . 2nd ed., London and Basingstoke:The Macmillan Press Ltd. Revised and enlarged edition. First edition 1962. Reprinted with alterations 1964. Reprinted 1979. ↩ 31

Erskine, Ralph. 1988. "Naval Enigma: The Breaking of Heimisch and Triton." *Intelligence and National Security*, 3(1): 162–183. ↩ 3, 20, and 21

Erskine, Ralph. 1989. "Naval Enigma: A Missing Link." *International Journal of Intelligence and Counter Intelligence*, 3(4): 493–508. ↩ 7

Erskine, Ralph. 1992. "The German Naval Grid in World War II." *Cryptologia*, 16(1): 39–51. ↩ 8

Erskine, Ralph, and Frode Weierud. 1987. "Naval Enigma: M4 and its Rotors." *Cryptologia*, 11(4): 235–244. ↩ 10

Erskine, Ralph, and Philip Marks. 2004. "Naval Enigma: Seahorse and Other Kriegsmarine Cipher Blunders." *Cryptologia*, 28(3): 211–241. ↩ 20 and 63

Federle, Jonathan, Dominic Rohner, and Moritz Schularick. 2024. "Who Wins Wars?" *Available at SSRN 5093393*. ↩ 5

Fetzer, Thiemo, Pedro CL Souza, Oliver Vanden Eynde, and Austin L Wright. 2021. "Security Transitions." *American Economic Review*, 111(7): 2275–2308. ↩ 5

Flanders Marine Institute. 2018. *IHO Sea Areas, Version 3.* Available online at https://www.marineregions.org/, https://doi.org/10.14284/323 (accessed September 22nd, 2022). ↩ 63

Flanders Marine Institute. 2021. *Global Oceans and Seas, Version 1.* Available online at https://www.marineregions.org/, https://doi.org/10.14284/542 (accessed September 22nd, 2022). ↩ 63

Glitz, Albrecht, and Erik Meyersson. 2020. "Industrial Espionage and Productivity." *American Economic Review*, 110(4): 1055–1103. ↩ 6

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277. ↩ 24

Gröner, Erich. 1990. *German Warships, 1815-1945: U-Boats and Mine Warfare Vessels.* Vol. 2, Naval Institute Press. ↩ 42

Guglielmo, Mark. 2008. "The Contribution of Economists to Military Intelligence during World War II." *The Journal of Economic History*, 68(1): 109–150. ↩ 6

Hague, Arnold. 2000. *The Allied Convoy System 1939–1945: Its Organization, Defence and Operation.* Vanwell. ↩ 14

Hainmueller, Jens. 2012. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies." *Political Analysis*, 20(1): 25–46. ↩ 28

Hess, Gregory D, and Athanasios Orphanides. 1995. "War Politics: An Economic, Rational-Voter Framework." *American Economic Review*, 85(4): 828–846. ↩ 5

Hileman, Garrick. 2017. "Currency black markets and historical turning points: ‚ÄòFree‚Äô sterling in new york and switzerland in the 1940s." *Working Paper*. ↩ 77

Hinsley, Francis Harry. 1979. *British Intelligence in the Second World War.* Vol. 1, Cambridge University Press. ↩ 84

Hinsley, Francis Harry. 1981. *British Intelligence in the Second World War.* Vol. 2, Cambridge University Press. ↩ 7

Hinsley, Francis Harry. 1984. *British Intelligence in the Second World War.* Vol. 3, Part I, Cambridge University Press. ↩ 63

Hinsley, Fred H. 1990. "British Intelligence in the Second World War: An Overview." *Cryptologia*, 14(1): 1–10. ↩ 9

Imbens, Guido W, and Donald B Rubin. 2015. *Causal Inference in Statistics, Social, and Biomedical Sciences.* Cambridge University Press. ↩ 25 and 28

Jackson, Matthew O, and Stephen Nei. 2015. "Networks of Military Alliances, Wars, and International Trade." *Proceedings of the National Academy of Sciences*, 112(50): 15277–15284. ↩ 5

Kahn, David. 1991. *Seizing the Enigma: The Race to Break the German U-boat Codes, 1939-1943.* ↩ 7, 30, and 40

Knowles, Kenneth. 1977. "Ultra and the Battle of the Atlantic: The American View." U.S. Naval Academy in Annapolis on October 28, 1977. ↩ 9, 30, and 32

Kohnen, David. 1999. *Commanders Winn and Knowles: Winning the U-boat War with Intelligence, 1939-1943.* Enigma Press. ↩ 8, 9, 32, and 33

Kohnen, David. 2019. "The Cruise of U-188: Special Intelligence and the "Liquidation" of Group Monsoon, 1943–1944." In *Decision in the Atlantic: The Allies and the Longest Campaign of the Second World War*. , ed. Marcus Faulkner and Christopher M. Bell, Chapter 10. University Press of Kentucky. ↩ 9, 20, 29, and 33

Li, Fan, Laine E Thomas, and Fan Li. 2019. "Addressing Extreme Propensity Scores via the Overlap Weights." *American Journal of Epidemiology*, 188(1): 250–257. ↩ 28

Martin, Philippe, Thierry Mayer, and Mathias Thoenig. 2008. "Make Trade not War?" *Review of Economic Studies*, 75(3): 865–900. ↩ 1 and 5

Mulligan, Timothy P. 1985. "The German Navy Evaluates Its Cryptographic Security, October 1941." *Military Affairs*, 49(2): 75–79. ↩ 42

Naval History Division. 1963. *United States Submarine Losses in World War II.* Washington, D.C. [Revised 2017]. ↩ 63

Rapping, Leonard. 1965. "Learning and World War II Production Functions." *Review of Economics and Statistics*, 81–86. ↩ 42

Ratcliff, Rebecca A. 1999. "Searching for Security: The German Investigations into Enigma's Security." In *Allied and Axis Signals Intelligence in World War II.* , ed. David Alvarez, 146–167. Frank Cass. ↩ 10, 42, and 43

Rexer, Jonah M. 2025. "Corruption as a Local Advantage: Evidence from the Indigenization of Nigerian Oil." *American Economic Review*, 115(3): 1019–57. ↩ 24

Rohwer, Jürgen. 1979. *Die Funkaufklärung und ihre Rolle im Zweiten Weltkrieg: e. internat. Tagung in Bonn-Bad Godesberg u. Stuttgart vom 15.-18. November 1978.* Motorbuch-Verlag. ↩ 19, 20, and 21

Rohwer, Jürgen. 1988. *Allied and Axis Radio-Intelligence in the Battle of the Atlantic: A Comparative Analysis.* ↩ 20

Rohwer, Jürgen. 1999. "Axis Submarine Successes of World War Two: German, Italian and Japanese Submarine Successes, 1939-1945." ↩ 9, 13, and 63

Rohwer, Jürgen, and Gerhard Hümmelchen. 2005. *Chronology of the War at Sea, 1939-1945: The Naval History of World War Two.* Chatham. 3rd Revised Edition. ↩ 14

Rozenas, Arturas, Roya Talibova, and Yuri M Zhukov. 2024. "Fighting for tyranny: State repression and combat motivation." *American Economic Journal: Applied Economics*, 16(3): 44–75. ↩ 6

Sebag-Montefiore, Hugh. 2000. "Enigma: The Battle for the Code." ↩ 7 and 52

SIPRI. 2025. "Trends in World Military Expenditure, 2024." Stockholm International Peace Research Institute (SIPRI) SIPRI Fact Sheet. ↩ 1

Smith, Christopher. 2021. "Bletchley Park and Big Science: Industrialising the Secret War, 1939-1945." *Journal of Intelligence History*, 20(2): 109–125. ↩ 5 and 41

Sonin, Konstantin, and Austin L Wright. 2024. "Rebel Capacity, Intelligence Gathering, and Combat Tactics." *American Journal of Political Science*, 68(2): 459–477. ↩ 5

Spolaore, Enrico, and Romain Wacziarg. 2016. "War and Relatedness." *Review of Economics and Statistics*, 98(5): 925–939. ↩ 5

Syrett, David. 1998. *The Battle of the Atlantic and Signals Intelligence: U–Boat Situations and Trends, 1941–1945.* Ashgate. ↩ 18 and 29

Syrett, David. 1999. "Communications Intelligence and the Sinking of the U-860, April-June 1944." *The Mariner's Mirror*, 85(1): 68–75. ↩ 7, 8, 23, and 43

Syrett, David. 2002. "The Infrastructure of Communications Intelligence: The Allied D/F Network and the Battle of the Atlantic." *Intelligence and National Security*, 17(3): 163–172. ↩ 8

Thompson, Peter. 2001. "How Much Did the Liberty Shipbuilders Learn? New Evidence for an Old Case Study." *Journal of Political Economy*, 109(1): 103–137. ↩ 42

Thornton, Rebecca Achee, and Peter Thompson. 2001. "Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding." *American Economic Review*, 91(5): 1350–1368. ↩ 42

US Congress. 2024. "Intelligence Community Spending Trends." Congressional Research Service R44381. ↩ 1

Wallis, W Allen. 1980. "The Statistical Research Group, 1942–1945." *Journal of the American Statistical Association*, 75(370): 320–330. ↩ 6

Walters, Christopher. 2024. "Empirical Bayes methods in labor economics." In *Handbook of Labor Economics*. Vol. 5, 183–260. Elsevier. ↩ 30

Williams, Greg H. 2014. *The Liberty Ships of World War II: A Record of the 2,710 Vessels and Their Builders, Operators and Namesakes, with a History of the Jeremiah O'Brien.* McFarland. ↩ 5, 40, and 42

Wintrobe, Ronald. 1998. *The Political Economy of Dictatorship.* Cambridge University Press. ↩ 43

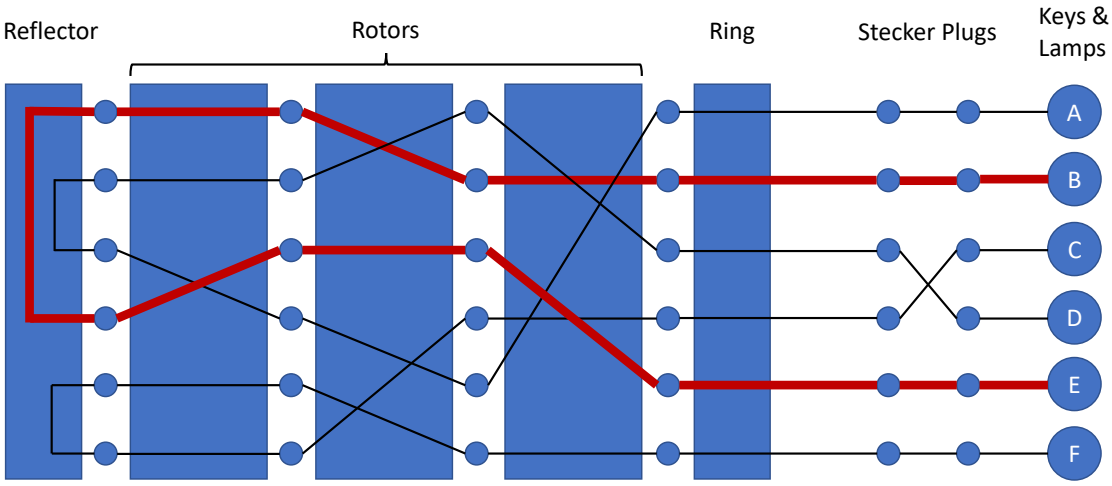
Wright, John. 2017. "The Turing Bombe Victory and the First Naval Enigma Decrypts." *Cryptologia*, 41(4): 295–328. ↩ 3 and 21

Wu, Yuxin, Alexander Kirillov, Francisco Massa, Wan-Yen Lo, and Ross Girshick. 2019. "Detectron2." *https://github.com/facebookresearch/detectron2*. ↩ 64

Appendices

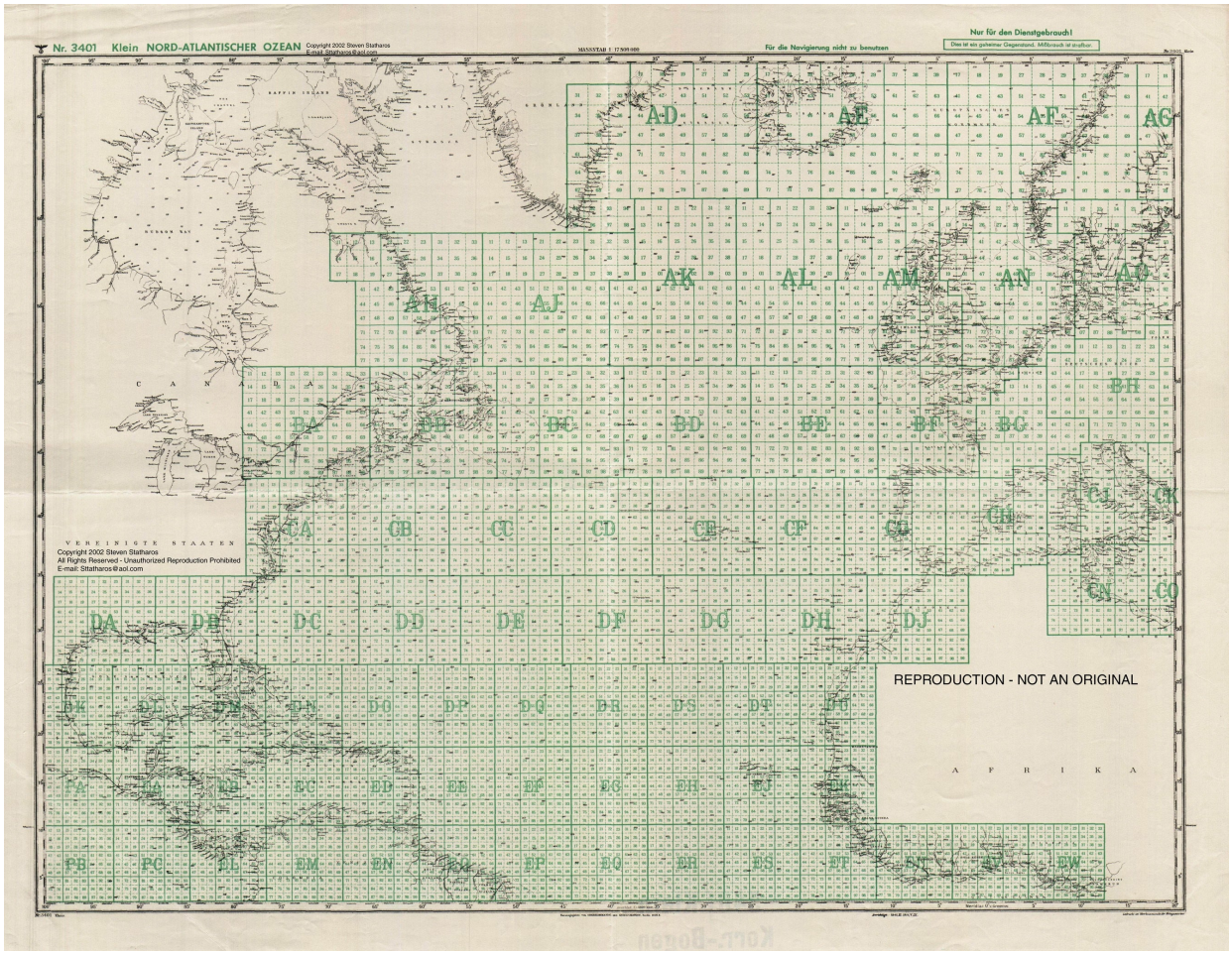
A Illustrations

Figure A1: Simplified Enigma Illustration.



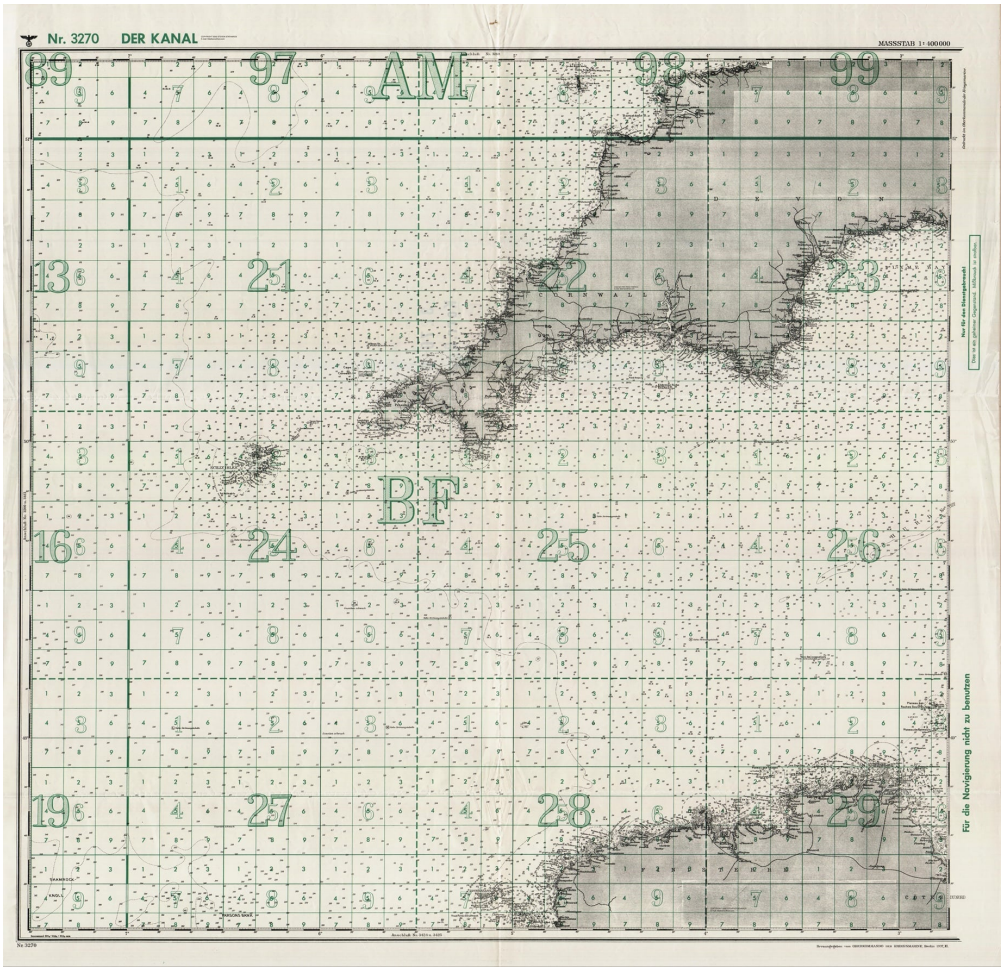
Notes: Simplified illustration of internal Enigma mechanics. Adapted from Budiansky (2000, p. 72) and Sebag-Montefiore (2000, p. 35). The operator first pressed keys in plain text. A single character would first run through the outer settings (stecker plugs), then the inner settings (ring and rotors), and back to illuminate the encoded letter lamp. After each letter, one or two rotors would advance a position at a time.

Figure A2: Grid Map North Atlantic.



Notes: Nazi grid map of the North Atlantic (broad tile structure).

Figure A3: Grid Map English Channel.



Notes: Nazi grid map of the English Channel (smallest tile structure).

B A Simple Model

Setup. There are two agents, the Allies and the Nazis. The Allies can be of two types, high (θ^H) or low (θ^L) capacity, with the probability of being the high type denoted by $0 < p < 1$. Essentially, we can interpret the high type as being able to read communications while the low type cannot. The Allies pursue actions s. One interpretation of s could be the number of merchant ships the Allies aim to save or U-boats to sink. However, these actions entail type-dependent costs. Both high- and low-type Allies can theoretically save/sink the same number of ships/U-boats, but the associated costs differ. More precisely, the Allies' direct flow utility is given by

$$U_A(s) = s - \frac{1}{2\theta^i}s^2.$$

In a one-period setting, the Allies would choose $s^i = \theta^i$ to maximize utility. Assuming $\theta^H > \theta^L$, the high type chooses a higher level of s.

While the Allies choose s ships to save/U-boats to sink, the actual realization is subject to additive random shocks. The realized number of ships saved or U-boats sunk is given by

$$z = s + \varepsilon,$$

where ε is drawn from a uniform distribution with boundaries $[-\phi/2, \phi/2]$. I assume that the support is sufficiently large, specifically $\phi > \theta^H - \theta^L$. While ε is a summary term, it captures uncertainties from various sources. Weather conditions, such as storms, fog, or rough seas, can disrupt both offensive and defensive naval operations. Other contributing factors include mechanical malfunctions or logistical issues. In the model, Nazis only observe the realized outcome z.

The model consists of two periods. The sequencing is as follows. First, the Allies are assigned a type and determine an action level s_1 in period 1. The Nazis then observe z (where I omit the subscript for convenience). Before period 2 begins, the Nazis can either invest in a security upgrade at a fixed cost c or not. The upgrade can essentially be viewed as a new encryption system. If the investment is made, the Allies attain the low-type cost structure in the second

period, regardless of their actual type. If the Nazis do not invest, the Allies retain their initial cost structure. After the publicly observed investment decision, the Allies again optimize their flow utility. However, from the perspective of period 1, utility in period 2 is discounted by a factor β. The Nazis' expected payoff in period 2 is given by

$$U_N(c) = -s_2 - c,$$

while their period 1 payoff does not affect decision-making. Finally, I impose the following restriction on the cost parameter:

$$p(\theta^H - \theta^L) < c < \theta^H - \theta^L.$$

The lower bound ensures that the Nazis do not always invest in the encryption upgrade regardless of Allied behavior. The upper bound ensures that the cost is sufficiently low such that the Nazis will invest when the Allies are certainly high-type. I return to this restriction below.

Equilibrium definition. I define an equilibrium as a set of strategies by the Allies and the Nazis that consitute best responses to each other, along with beliefs held by the Nazis that map all signals to a Bayesian posterior over the Allies' type.

Preliminaries. We begin by noting that the low-type will select $s_1^L = s_2^L = \theta^L$ in both periods. Since the low-type's cost structure remains unchanged, the Nazis' investment choice does not affect their payoff. The high type's second-period choice, however, depends on whether the Nazis upgrade. If the Nazis invest after the first period, the high type adopts the low-type cost structure and chooses $s_2^H = \theta^L$. If no upgrade occurs, the high type instead chooses $s_2^H = \theta^H$, yielding a higher payoff:

$$U_A(\theta^H) - U_A(\theta^L) = 0.5(\theta^H - \theta^L).$$

Now, consider the high type's decision in the first period. Anticipating this potential benefit, they are incentivized to deviate from the one-period optimum. Specifically, by choosing $s_1^H < \theta^H$ they may reduce the probability of a Nazi upgrade. We further note that the high type has no

incentive to choose a level above the one-period optimum, as doing so would render the Allies unambiguously worse off. Additionally, the high type's choice is bounded from below by θ^L. Selecting s below this threshold will not affect the upgrading probability but will decrease utility.

Given these observations, Figure B1 illustrates the range of possible signals. The low type chooses $s_1^L = \theta^L$, while the high type selects some $s_1^H \in [\theta^L, \theta^H]$ in period 1.

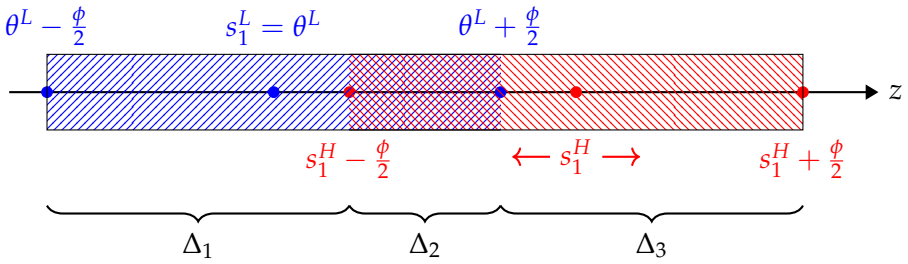


Figure B1: Range of signals.

We see that the resulting signal space can essentially be partitioned into three ranges (Δ_1, Δ_2, Δ_3). Signals falling within each partition correspond to different posterior beliefs $\gamma(z)$ about the Allies being high-type. Notably, there exists an overlapping signal range Δ_2 in which the posterior $\gamma(z)$ equals the prior probability p. This overlap arises from the assumption that the noise support is sufficiently large. The reason the posterior equals the prior in this region is that the noise is drawn from uniform distributions with equal densities. Additionally, the posterior belief equals zero in partition Δ_1 and one in partition Δ_3 (Figure B2).

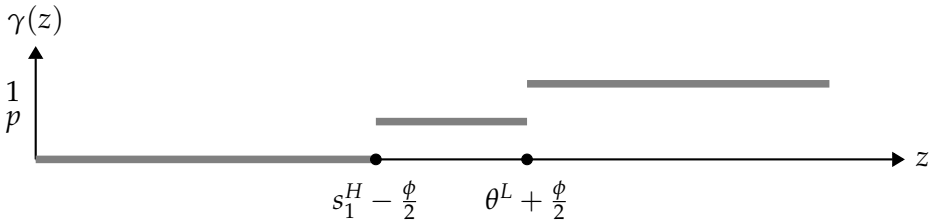


Figure B2: Nazi posterior belief about the Allied being the high-type.

Derivations. I proceed by characterizing an equilibrium in which high-type Allies exercise restraint—that is, they choose an s_1^H lower than the myopic optimum. First, let the Nazis follow a threshold rule. Suppose they upgrade whenever they observe signals larger than some z^*. The probability

that the Allies *avoid* an upgrade is given by

$$Pr(z < z^*) = Pr(s_1 + \varepsilon < z^*) = Pr(\varepsilon < z^* - s_1).$$

The associated cumulative distribution function is

$$F(z^* - s_1) = \begin{cases} 0, & z^* - s_1 < -\frac{\phi}{2}, \\ \frac{1}{\phi}(z^* - s_1 + \frac{\phi}{2}), & -\frac{\phi}{2} \leq z^* - s_1 \leq \frac{\phi}{2}, \\ 1, & z^* - s_1 > \frac{\phi}{2}. \end{cases}$$

I illustrate the probability as a function of s_1 in Figure B3. If the Allies choose for instance $s_1 = z^*$, the Nazis will upgrade with a 0.5 probability. The upgrading decision will depend on the realization of ε.

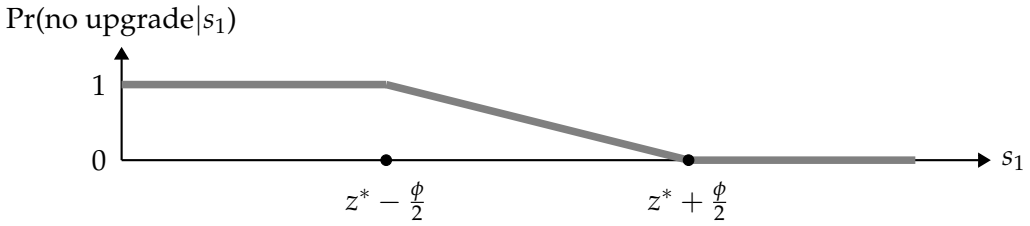


Figure B3: Probability of avoiding an upgrade.

Given that the Nazis follow a z^*-threshold rule, we proceed by computing the Allies' optimal strategy. The high-type Allies' best response is:

$$s_1^*(z^*) = \arg\max_{s_1} \left\{ \underbrace{s_1 - \frac{1}{2\theta^H} s_1^2}_{\text{first period}} + \beta \underbrace{[F(z^* - s_1)]}_{\text{prob. staying H}} \underbrace{0.5\left(\theta^H - \theta^L\right)}_{\text{benefit of staying H}} \right\}.$$

Taking the first-order condition,

$$\frac{d}{ds_1}\left(s_1 - \frac{1}{2\theta^H} s_1^2 + \beta F(z^* - s_1) \cdot 0.5(\theta^H - \theta^L)\right) = 0,$$

and assuming a parameterization consistent with an interior solution, optimization yields

$$s_1^{H^*} = \theta^H \left[1 - \beta \frac{\theta^H - \theta^L}{\phi} \frac{1}{2}\right],$$

which is smaller than θ^H.

Next, we consider the Nazis' best response. Suppose the Nazis correctly conjecture that the Allies optimally choose s_1 in both states of the world. What, then, is their optimal cutoff value z^*? Nazi utility is given by

$$U_N(\text{upgrade, no upgrade}) = \begin{cases} -\theta^L - c & \text{if upgrade,} \\ -(\gamma(z)\theta^H + (1-\gamma(z))\theta^L) & \text{if no upgrade.} \end{cases}$$

The Nazis will choose to upgrade whenever the expected cost of facing a high-type in period 2 exceeds the cost of upgrading c, i.e., when:

$$-\theta^L - c \geq -(\gamma(z)\theta^H + (1-\gamma(z))\theta^L)$$

Rearranging yields the following threshold condition:

$$\gamma(z) \geq \frac{c}{\theta^H - \theta^L}.$$

To determine when this condition holds, we use the belief function $\gamma(z)$. The belief that the Allies are high-type, conditional on Allied strategy $s_1^{H^*}$, is determined via Bayes' Rule,

$$\gamma(z) = \begin{cases} 0, & z < s_1^{H^*} - \frac{\phi}{2}, \\ p, & s_1^{H^*} - \frac{\phi}{2} \leq z < \theta^L + \frac{\phi}{2}, \\ 1, & \theta^L + \frac{\phi}{2} \leq z. \end{cases}$$

Since $\gamma(z)$ takes only three values, we need to evaluate only two cases: $\gamma(z) = p$ and $\gamma(z) = 1$. First, consider the case where $\gamma(z) = p$, which occurs for all signals $s_1^{H^*} - \frac{\phi}{2} \leq z < \theta^L + \frac{\phi}{2}$. The

Nazis would upgrade in this range if

$$p \geq \frac{c}{\theta^H - \theta^L},$$

and the associated threshold signal would be determined by $z^* = s_1^{H*} - \frac{\phi}{2}$. However, this cannot constitute an equilibrium. The reason is that the equilibrium threshold will lead the high-type Allies to always face an upgrade—despite choosing a lower s_1 than the myopic optimum. As a result, they are better off deviating. This also rationalizes the initial assumption on the lower bound of the cost parameter c:

$$p(\theta^H - \theta^L) < c.$$

Second, consider the case where the posterior belief is $\gamma(z) = 1$. The Allies are known with certainty to be high-type for all signals $z \geq \theta^L + \frac{\phi}{2}$. The Nazis will choose to upgrade if

$$1 \geq \frac{c}{\theta^H - \theta^L} \Leftrightarrow c \leq \theta^H - \theta^L,$$

which establishes the upper bound on the cost parameter. We attain an equilibrium in which high-type Allies exercise restraint—that is, they do not choose the one-period optimum. The Nazis' optimal cutoff value is then given by:

$$z^* = \theta^L + \frac{\phi}{2}.$$

Equilibrium. An equilibrium consistent with the historical record is characterized by the following conjectures and decision rules. The Nazis adopt a cutoff rule, engaging in costly upgrading only if the observed noisy action level exceeds the threshold $z^* = \theta^L + \frac{\phi}{2}$. The low-type Allies conform to $s^{L*} = \theta^L$ in both periods. Assuming a parameterization consistent with an interior solution, the high-type Allies instead choose a first-period level of $s_1^{H*} = \theta^H \left[1 - \beta \frac{\theta^H - \theta^L}{\phi} \frac{1}{2}\right] < \theta^H$, thereby exhibiting strategic restraint. This essentially formalizes the idea of under-utilization of intelligence capacity. In the second period, high-type Allies choose $s_2^{H*} = \theta^H$ if the Nazis do not invest in security, and $s_2^{H*} = \theta^L$ if they do.

Predictions. First, I define restraint as the wedge between s_1^{H*} and the myopic optimum θ^H.

1. Restraint decreases in noise. Consider rerouting merchant ships and sinking U-boats as distinct outcomes. The Nazis are fully aware of their U-boats—their states, positions, and related details—wheras their knowledge of merchant shipping is much more limited. How many merchant ships there are and how many ought to sink is much more opaque. In the model, we can characterize this through differing levels of noise variance ϕ, while remaining within the confines of an interior solution. Comparative statics yield:

$$\frac{\partial s_1^{H*}}{\partial \phi} = \frac{1}{2}\frac{\theta^H \beta(\theta^H - \theta^L)}{\phi^2} > 0.$$

As the noise support increases, so does s_1^{H*}. This implies that under-utilization of intelligence declines with greater uncertainty. Mapping this to the data, we should observe less restraint in rerouting and saving merchant ships, but greater restraint in sinking U-boats.

2. Restraint decreases over time. Consider β as the relative weight placed on the future. The weight is higher when the second period is expected to be longer and smaller when the end is near. Comparative statics reveal:

$$\frac{\partial s_1^{H*}}{\partial \beta} = -\frac{1}{2}\frac{\theta^H(\theta^H - \theta^L)}{\phi} < 0.$$

When the future carries greater weight—such as earlier in the war—we expect a smaller s_1^{H*}, reflecting a higher degree of under-utilization. As the end of the war approaches and β declines, so does strategic restraint.

3. Restraint increases in the relative value of retaining/losing Enigma intelligence. Consider an extended version of the model in which flow utility is given by:

$$U_A(s) = \gamma s - \frac{1}{2\theta^i}s^2,$$

where $\gamma > 0$ serves as a value shifter—capturing different valuations of saving ships or sinking submarines. The mypoic optimum then becomes $s^{i*} = \gamma\theta^i$, and the benefit of retaining the high-type cost structure in the second period becomes $\frac{1}{2}\gamma^2[\theta^H - \theta^L]$. An increase in γ thus raises the

relative cost of revealing high-type status, as the forgone benefit in the second period becomes more valuable.

The empirical analogy lies in the differing strategic valuations between British and American forces. For the United Kingdom, disruptions to the Atlantic supply line plausibly loomed larger than for the United States. Normalizing $\gamma_1 = 1$ in the first period, comparative statics yield:

$$\frac{\partial s_1^{H^*}}{\partial \gamma_2} = -\beta \gamma_2 \theta^H \frac{(\theta^H - \theta^L)}{\phi} < 0.$$

This implies that higher relative valuations of losing Enigma intelligence increase the willingness to forgo immediate benefits in the first period. Accordingly, we would expect British forces to exhibit greater restraint in utilizing intelligence than their American counterparts.

C Data construction

C.1 Assigning vessels to the Shark network.

Data on sunk convoys were collected from https://uboat.net/ops/convoys/convoys.php. Based on the position of the loss, I assign convoys to the Shark U-boat network.[45] From the beginning of the war until February 1942, all U-boats were jointly on one communication network, the Dolphin network. After February 1942, all U-boats then transitioned to the Shark network, except those that were stationed in the Far North (Hinsley, 1984, Appendix 3). Beginning in June 1943, U-boats in the Mediterranean exited Shark and entered the Turtle network (Hinsley, 1984, Appendix 3). I exclude respective convoys from the time series. In October 1943, U-boats in the Black Sea migrated to the Grampus network and in February 1945, U-boats in the Far East entered Sunfish (Erskine and Marks, 2004). As before, I only keep convoys that were passaging through waters in which U-boats continued to communicate on the Shark network. Toward the end of the war, this mainly consisted of convoys in the Atlantic.

C.2 Sources

I collect data from a variety of sources.

Table C1: Data sources

Data	Source
Merchant ships hit by German Submarines	Uboat.net
Merchant ships hit by Italian Submarines	Uboat.net
Merchant ships hit by Japanese Submarines	Rohwer (1999)
Sunk German Submarines	Uboat.net
Sunk Italian Submarines	Uboat.net
Sunk Japanese Submarines	Naval History Division (1963) [2017]
Key breaking speed	Naval Section: Daily Bulletins (National Archives, Kew: HW 8/2)
Decrypts	Teleprinted Translations of Decrypted German U-Boat Traffic. December 1942-December 1945 (National Archives, Kew: DEFE 3/705-744)

[45] To map sunk convoys I use global oceans and seas shape files from the Flanders Marine Institute (2018, 2021).

C.3 Decrypts

Data processing. First, I collected all decrypt scans (n=43272) held at the National Archives, Kew. These are readily available online and can be downloaded after registration. Next, I used a random sample of 865 scans to classify picture segments using Roboflow. Segment classes were for instance "time of intercept" and "time of relay" (to the OIC). These data were then split into training (n=605), validation (n=174), and test (n=86) data sets. Next, I trained a segmentation model relying on the Detectron2 library (Wu et al., 2019) on Google Colab. After segmenting the original scans, I used Google Vision Control to extract the relevant text information from the picture segments.

To identify specified U-boats, I first created lists of patrolling U-boats/ commanders for each day over the analysis period (allowing for +2/-2 week deviations). I then employed a fuzzy-string search of commander names in the decrypts, as well as U-boat numbers. To identify decrypts with and without specific location information I created a dummy recording unity if a decrypt mentioned "position", "square" or "degree". Prior manual inspection of decrypts revealed that grid point information was almost always accompanied by one of these terms. This approach avoids incorrectly recording random OCR output as grid point coordinates. Finally, for time information, I extracted the "time of relay" and the "time of intercept" using Regex. Time of relay captures when decrypts were sent to the OIC (British time zone), essentially when they became operationally valuable. The time of intercept denotes when the encrypted text was received at radar stations (British time zone). Some decrypts also include a time of origin, denoting the signal origin in German time. Typically the time of origin and time of intercept were within the same hour. Thus, in case of missing intercept time, I impute using the time of origin.

For validation, I cross-checked the algorithmic output with a random sample of 100 manually coded decrypts.

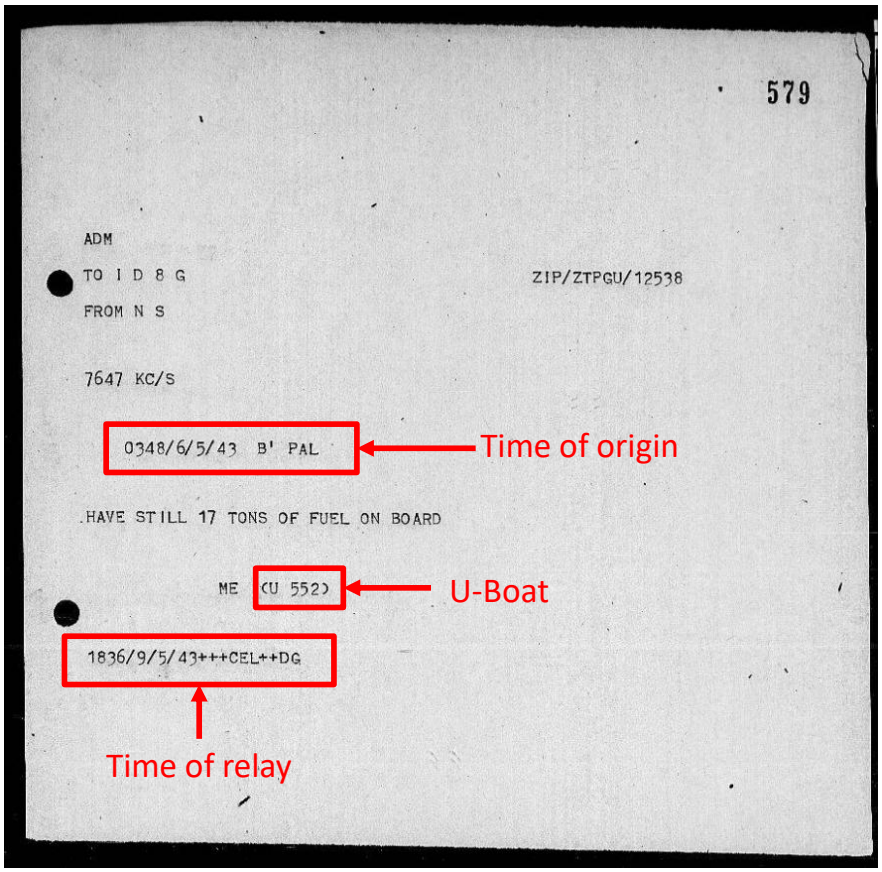
- U-boats
  - Manually: identified 94 U-boats
  - Algorithm: 82 correctly identified, 6 false entries, 12 missing
- Position revelations
  - Manually: 47 identified position reports

  - Algorithm: 42 correctly identified, 0 false entries, 5 missing
- Time of relay
  - Manually: 92 identified time reports
  - Algorithm: 82 correctly identified, 0 false entries, 10 missing
- Time of intercept
  - Manually: 96 identified time reports
  - Algorithm: 91 correctly identified, 1 false entry, 4 missing

To provide some intuition for errors in data processing, among the 6 false positives in U-boats, 4 were related to Josef *Will*. The string "will" appeared in four messages as a verb. All missing position reports stem from position reports that did not relate to Reichsmarine grid points, but instead to longitude/latitude coordinates. Missings in the time of relay/intercept stem broadly from segmentation and OCR errors. The few OCR errors occur mainly due to poor scan quality and (hand-written) corrections overwriting machine-typed text.

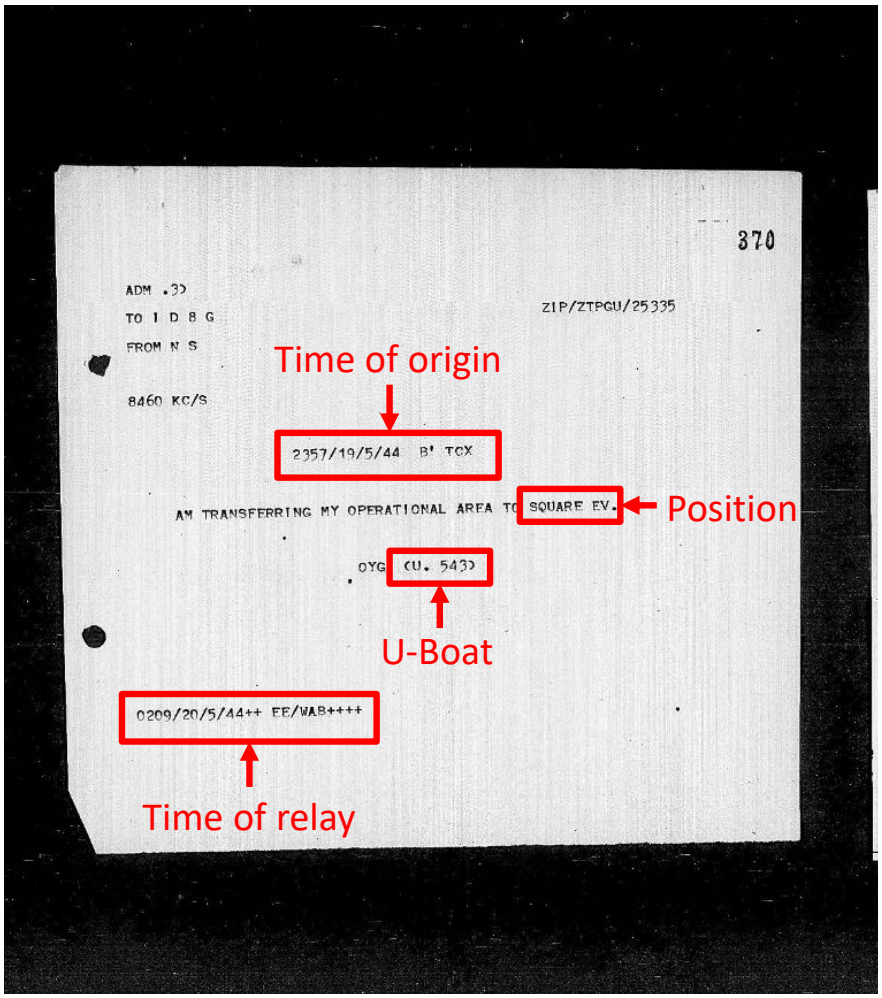
Examples. Examples of decrypt scans are provided below.

Figure C1: Example: Decrypt I.



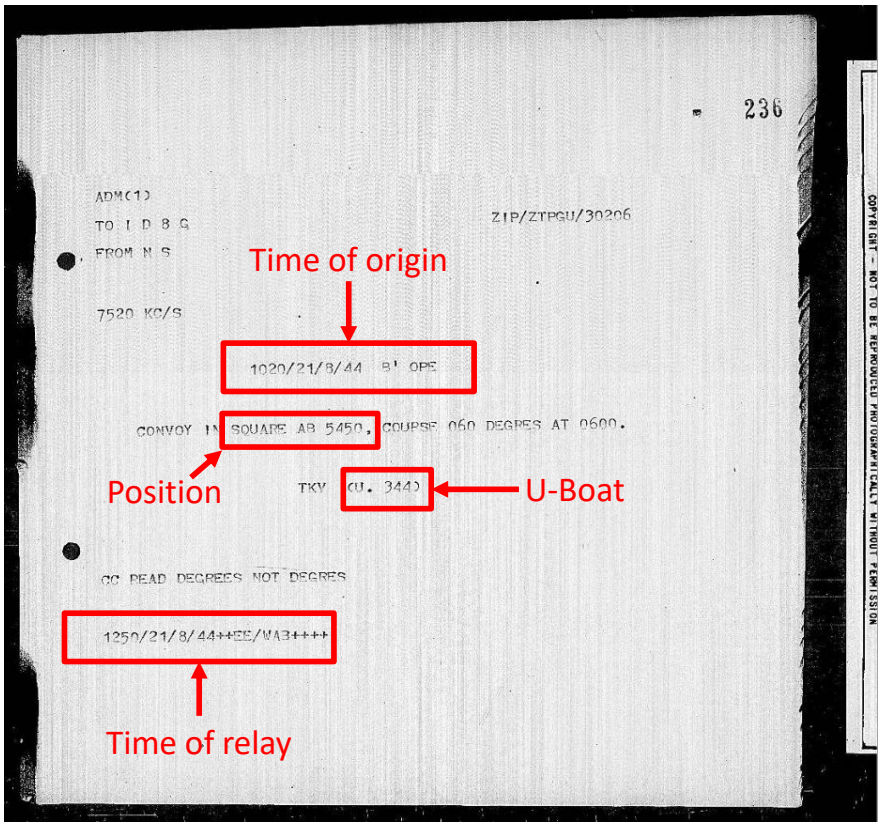
Notes: Decrypted message (National Archives, Kew: DEFE 3/717/582).

Figure C2: Example: Decrypt II.



Notes: Decrypted message (National Archives, Kew: DEFE 3/730/372).

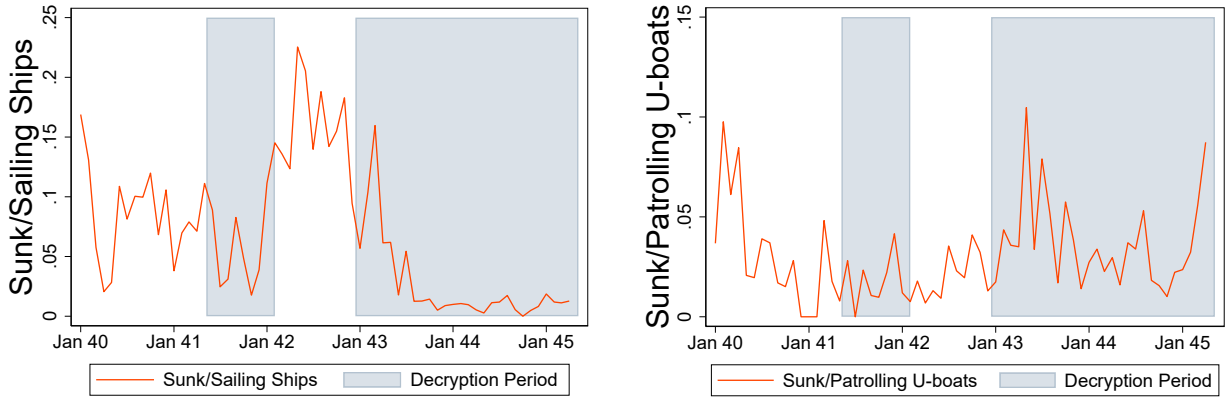
Figure C3: Example: Decrypt III.



Notes: Decrypted message (National Archives, Kew: DEFE 3/735/243).

D Further results and robustness

Figure D1: Share of sunk merchant ships and U-boats over time.

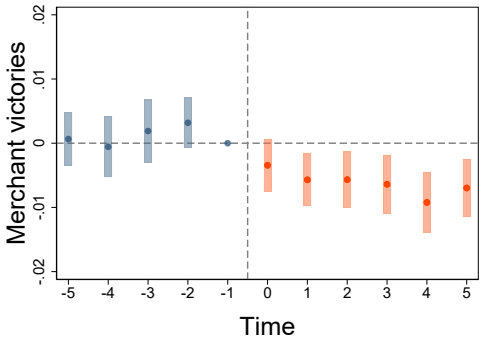


(a) Share sunk merchant ships

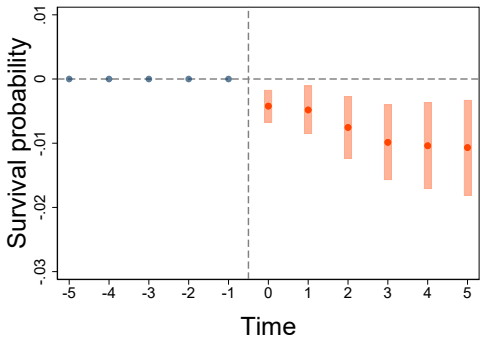
(b) Share sunk U-boats

Notes: Left-hand panel presents the number of sunk merchant ships over ships sailing in convoys binned by months. The right-hand side shows the number of sunk U-boats over patrolling U-boats binned by months. The shaded areas indicate periods in which Enigma messages were largely decrypted.

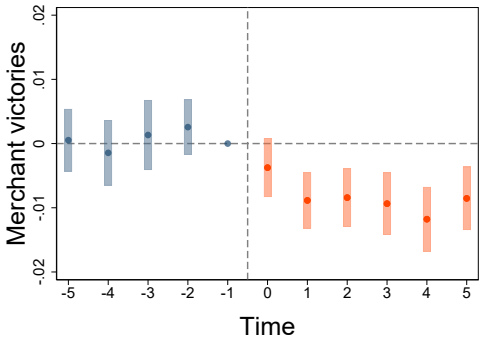
Figure D2: Revealing positions: robustness to refined treatment definitions.



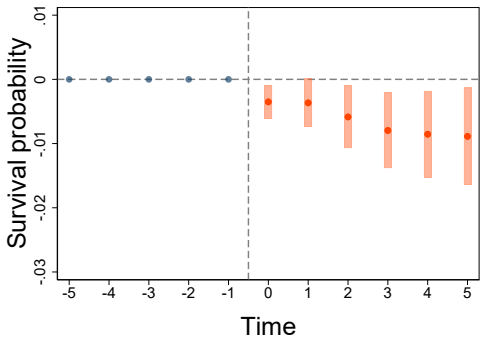
(a) Merchant ships: omitting "assist*" decrypts



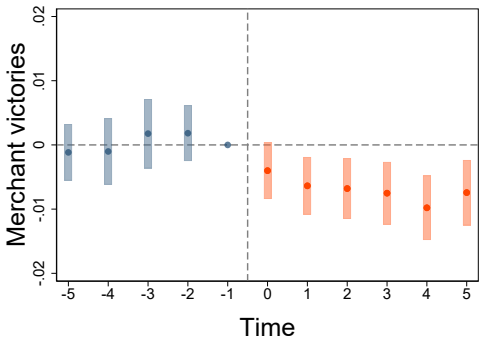
(b) U-boat survival: omitting "assist*" decrypts



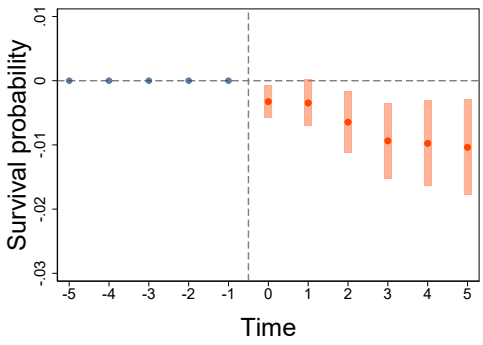
(c) Merchant ships: omitting "attack*" decrypts



(d) U-boat survival: omitting "attack*" decrypts



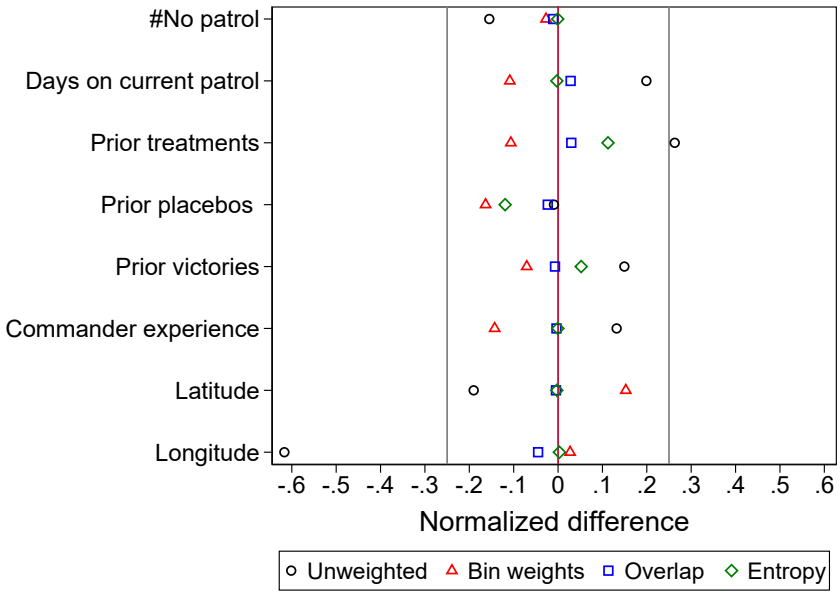
(e) Merchant ships: omitting "aircraft" decrypts



(f) U-boat survival: omitting "aircraft" decrypts

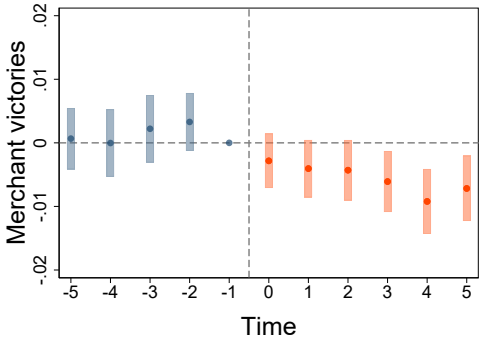
Notes: Left-hand panels present event study point estimates for the differences in victories over merchant vessels by revealed U-boats versus the clean control U-boats. Right-hand panels present survival probabilities. Each row refines the treatment definition. In Panels (a) and (b) the treatment are decrypts with location information that do not co-mention "assist*" strings. In Panels (c) and (d) the treatment are decrypts with location information that do not co-mention "attack*" strings. In Panels (e) and (f) the treatment are decrypts with location information that do not co-mention "aircraft." Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Figure D3: Covariate balance.

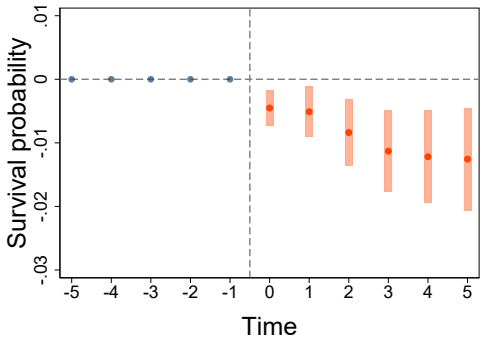


Notes: This Figure shows normalized differences in characteristics between treated and untreated U-boats subject to different weighting schemes. Covariates are measured at $t-1$, where t is a cohort's treatment day. The normalized difference is calculated as $\Delta = \frac{\bar{\mu}_t - \bar{\mu}_c}{\sqrt{(\sigma_t^2+\sigma_c^2)/2}}$, where $\bar{\mu}_t$ and $\bar{\mu}_c$ are sample means for a given covariate in the control and treatment groups. σ_t^2 and σ_c^2 are the associated sample variances.

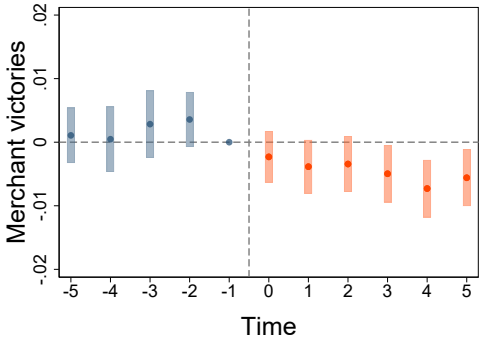
Figure D4: Revealing positions: robustness to different reweighting schemes.



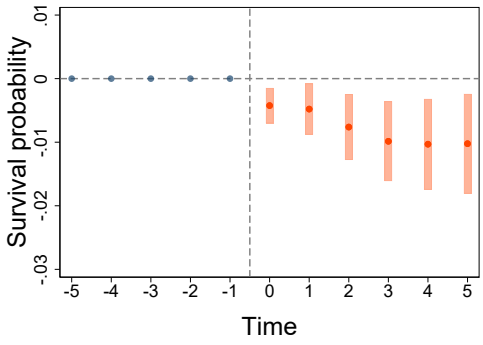
(a) Merchant ships: propensity score bin weights



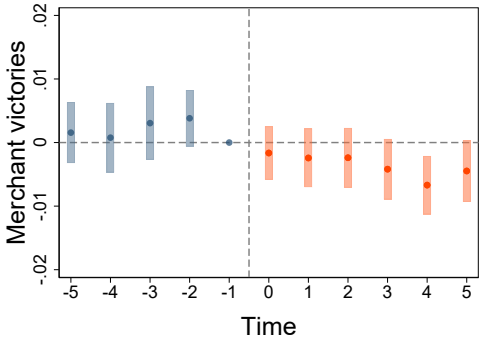
(b) U-boat survival: propensity score bin weights



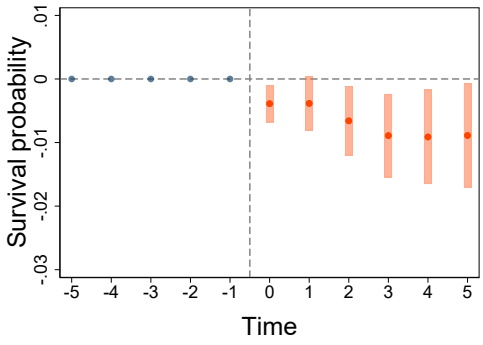
(c) Merchant ships: overlap weights



(d) U-boat survival: overlap weights



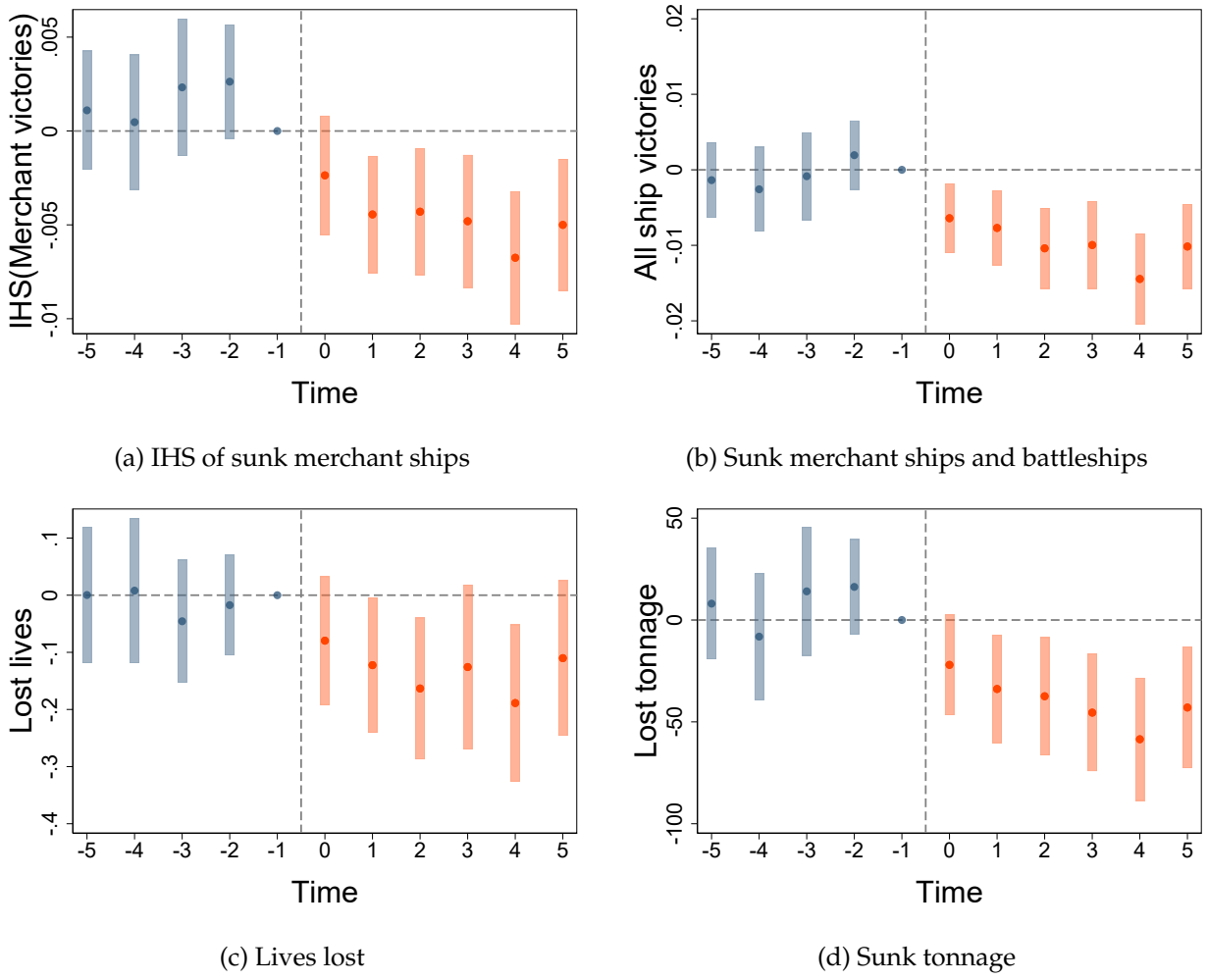
(e) Merchant ships: entropy balance weights



(f) U-boat survival: entropy balance weights

Notes: Left-hand panels present event study point estimates for the differences in victories over merchant vessels by revealed U-boats versus the clean control U-boats. Right-hand panels presents survival probabilities. Each row indicates different reweighting schemes. I use the following covariates to reweight: patrol number, days on current patrol, the number of previous location revelations, messages without geo-information, previously sunk merchant ships, commander experience in days, latitude, and longitude. Panels (a) and (b) reweight the control groups within twenty propensity score bins to attain balance in the number of treated and untreated observations. Panels (c) and (d) reweight using overlap weights. Panels (e) and (f) reweight using entropy balance. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Figure D5: Revealing positions: robustness to different measurements of Allied shipping losses.



(a) IHS of sunk merchant ships

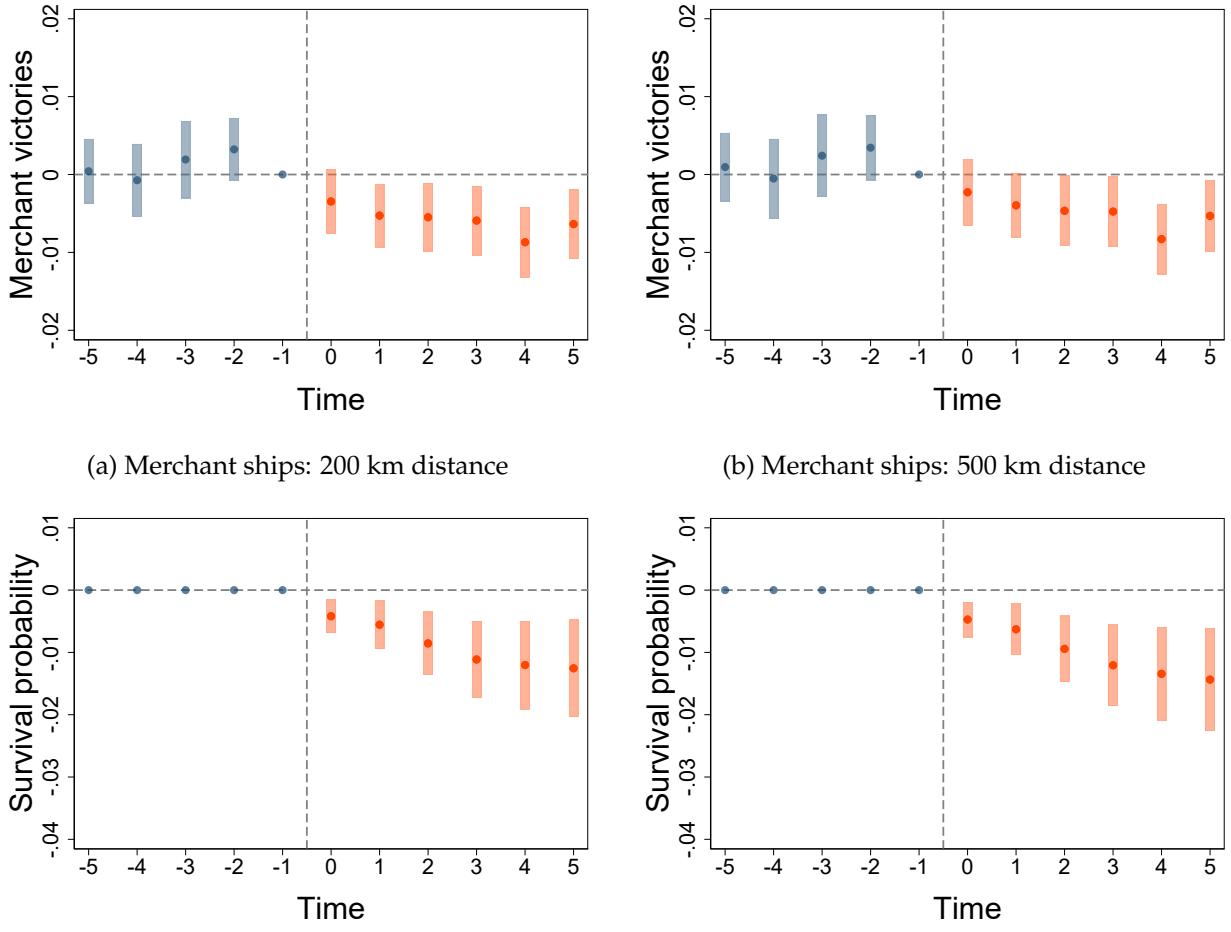
(b) Sunk merchant ships and battleships

(c) Lives lost

(d) Sunk tonnage

Notes: Panel (a) presents event study point estimates using the inverse hyperbolic sine of victories over merchant vessels as outcome. Panel b presents event study coefficients for the effect on all victories, including battleships. Panel (c) presents event study coefficients for the effect on merchant sailors' lives lost. Panel (d) presents event study coefficients for the effect on sunk merchant ship tonnage. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Figure D6: Revealing positions: robustness to geographic spillovers.



(a) Merchant ships: 200 km distance

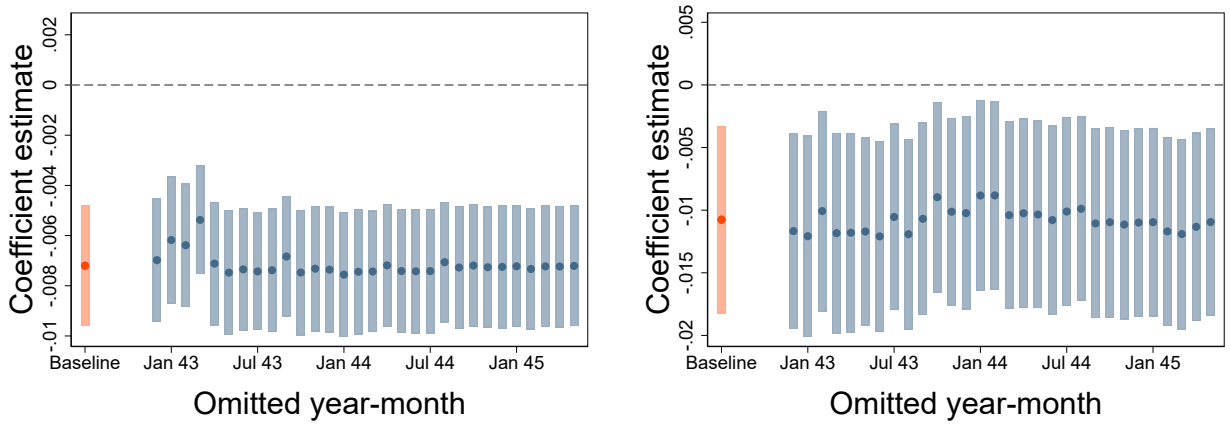
(b) Merchant ships: 500 km distance

(c) U-boat survival: 200 km distance

(d) U-boat survival: 500 km distance

Notes: Top panels present event study point estimates for the effect of decrypts on merchant shipping losses where control units are restricted to those that are at least 200 km or 500 km away from treatment units the day before treatment. Bottom panel presents estimates for the effect on survival. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Figure D7: Revealing positions: outlier sensitivity.

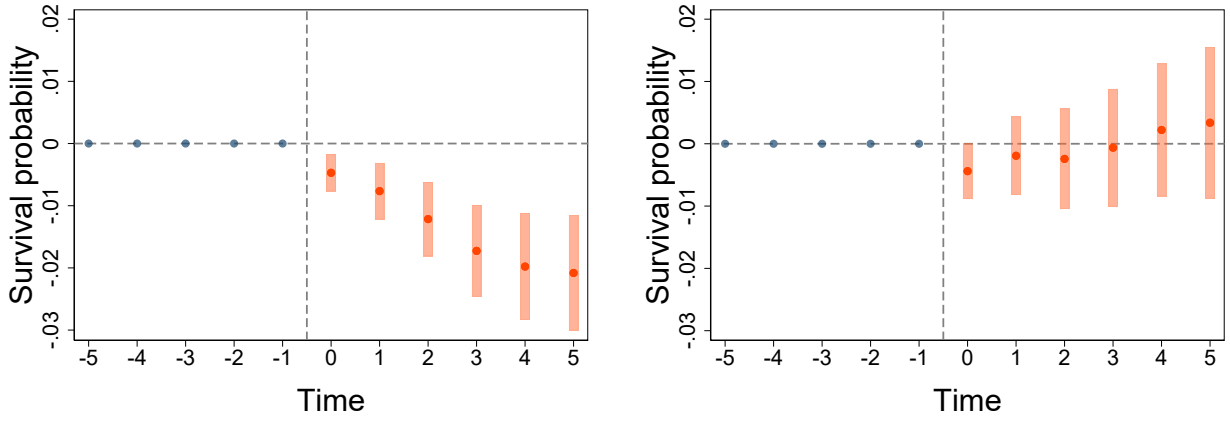


(a) Sunk merchant ships

(b) U-boat survival

Notes: I estimate coefficients on different subsamples, iteratively omitting U-boat cohorts from different year-months. Left-hand figure presents average treatment effects on victories over merchant ships before and after U-boats reveal locations. Right-hand figure presents survival probabilities five days after treatment occured. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Figure D8: Revealing positions: U-boat survival by captain quality (raw FE).

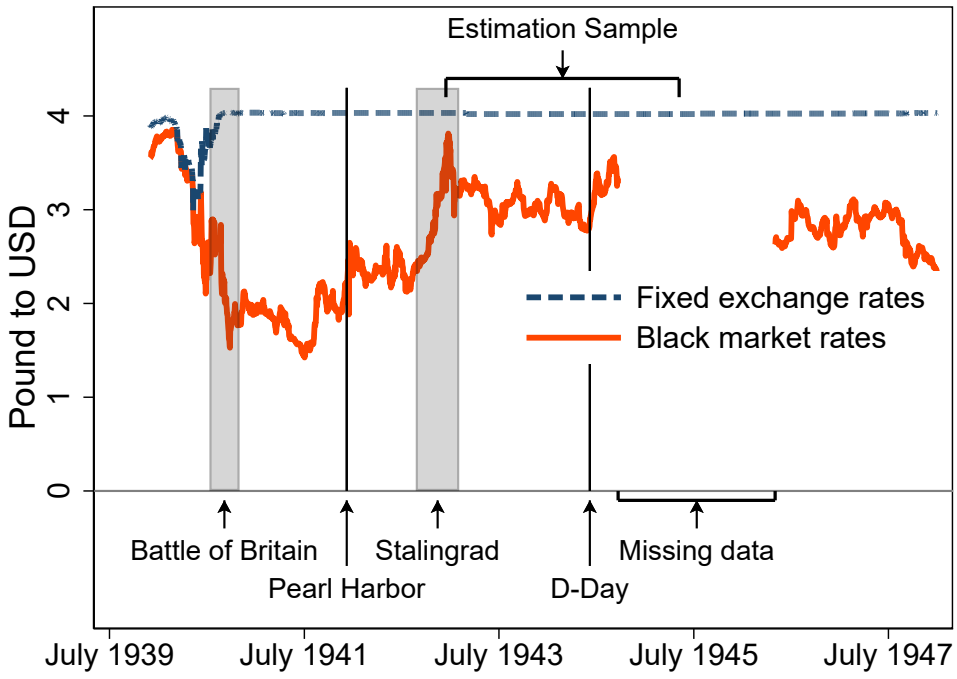


(a) Above-median fixed effects

(b) Below-median fixed effects

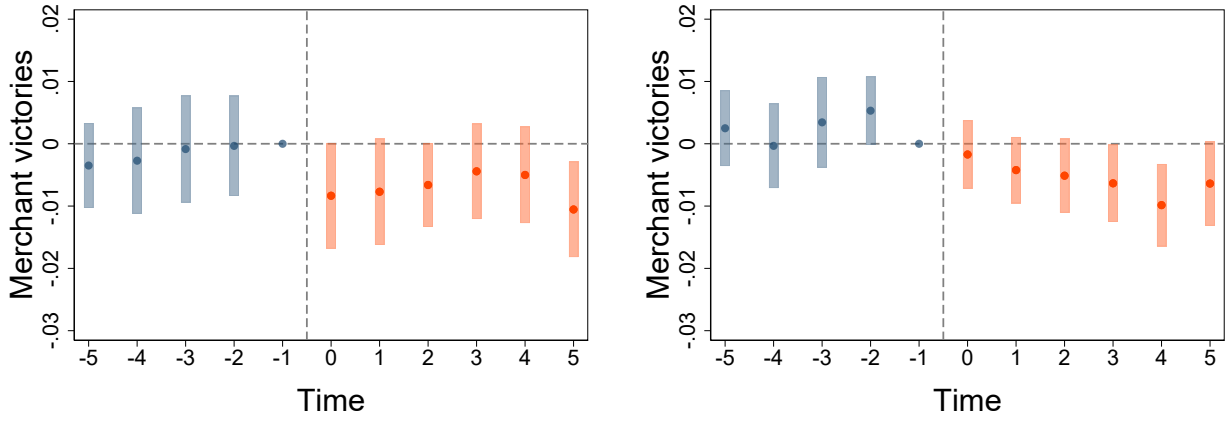
Notes: Figure presents event study point estimates for the differences in survival probabilities by revealed U-boats versus the clean control U-boats. The left-hand side shows estimates for above-median commanders in terms of raw merchant victory fixed effects. The right-hand side shows estimates for below-median commanders. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Figure D9: Allied winning probability proxied by Pound to USD black market rates.



Notes: This Figure shows Pound to USD "free" market rates from Switzerland as well as the official fixed exchange rates provided by Hileman (2017). Data were cross-validated with Eichengreen et al. (2024). Estimation sample indicates the time period underlying the decrypt-level analyses.

Figure D10: Revealing positions: merchant victories in different Atlantic zones.



(a) British waters

(b) American waters

Notes: Figure presents event study point estimates for the differences in victories over merchant vessels by revealed U-boats versus the clean control U-boats. The left-hand figure shows the effect on merchant losses in British-designated waters. The right-hand figure shows the effect on merchant losses in American-designated waters. Lines indicate 95 percent confidence intervals. Standard errors are clustered on U-boat-level.

Table D1: Two day cycle in key-breaking speed.

	Time to break			IHS(Time to break)		
	(1)	(2)	(3)	(4)	(5)	(6)
Paired settings	-8.268***	-8.246***	-8.137***	-0.270***	-0.268***	-0.265***
	[2.288]	[2.024]	[1.974]	[0.087]	[0.066]	[0.065]
Day FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No
Year-Month FE	No	No	Yes	No	No	Yes
R^2	0.024	0.266	0.307	0.018	0.452	0.471
Mean dep var	30.276	30.276	30.276	3.735	3.735	3.735
Observations	522	522	522	522	522	522

Notes: Unit of observation: day. Paired settings is a dummy variable attaining one on even calendar days. Time to break refers to the number of hours until daily Shark settings were identified. IHS is the inverse hyperbolic sine transformation of this value. Sample period November 1943 to May 1945. Robust standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D2: Two day cycle in decryption of messages.

	$\mathbb{1}$(Relayed within 12h)			IHS(Relay time)		
	(1)	(2)	(3)	(4)	(5)	(6)
Paired settings	0.059**	0.057***	0.058***	-0.234**	-0.222***	-0.224***
	[0.026]	[0.022]	[0.020]	[0.100]	[0.084]	[0.076]
Day FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No
Year-Month FE	No	No	Yes	No	No	Yes
R^2	0.005	0.136	0.213	0.006	0.216	0.336
Mean dep var	0.261	0.261	0.261	4.155	4.155	4.155
N Clusters	860	860	860	860	860	860
Observations	30922	30922	30922	30922	30922	30922

Notes: Unit of observation: decrypt. Paired settings is a dummy variable attaining one if the message was intercepted on even calendar days. Relay time refers to the difference in hours between interception and transmission to the OIC. I show correlations with a dummy for 'relayed within 12h' and with the inverse hyperbolic sine of the relay time. Sample covers messages intercepted between December 1942 to May 1945. Standard errors clustered by date.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D3: Two day cycle in outcomes.

	Sunk merchant ships			Sunk U-boats		
	(1)	(2)	(3)	(4)	(5)	(6)
Paired settings	-0.171*	-0.170*	-0.171**	0.043	0.045	0.046
	[0.095]	[0.089]	[0.085]	[0.051]	[0.049]	[0.048]
Day FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No
Year-Month FE	No	No	Yes	No	No	Yes
R^2	0.003	0.149	0.237	0.001	0.104	0.157
Mean dep var	0.746	0.746	0.746	0.446	0.446	0.446
Observations	1060	1060	1060	1060	1060	1060

Notes: Unit of observation: day. Paired settings is a dummy variable attaining one on even calendar days. Outcomes are the number of sunk Allied merchant ships and Nazi U-boats. Sample covers the periods in which U-boat Enigma codes were broken: August 1941 to January 1942 and December 1942 to May 1945. Robust standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D4: Placebo test: two day cycle in outcomes.

	Sunk merchant ships			Sunk U-boats		
	(1)	(2)	(3)	(4)	(5)	(6)
Paired settings	-0.114	-0.117	-0.117	0.014	0.014	0.015
	[0.129]	[0.118]	[0.115]	[0.025]	[0.024]	[0.024]
Day FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	Yes	No	No	Yes	No
Year FE	No	Yes	No	No	Yes	No
Year-Month FE	No	No	Yes	No	No	Yes
R^2	0.001	0.177	0.224	0.000	0.062	0.100
Mean dep var	1.821	1.821	1.821	0.115	0.115	0.115
Observations	1014	1014	1014	1014	1014	1014

Notes: Unit of observation: day. Paired settings is a dummy variable attaining one on even calendar days. Outcomes are the number of sunk Allied merchant ships and Nazi U-boats. Sample covers the periods in which U-boat Enigma codes were *not* broken: September 1939 to July 1941 and February 1942 to December 1942. Robust standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D5: Average treatment effects: Sunk merchant ships.

	Baseline	- Conv. mentioned	IHS	+ Battleships	P-score bin W	Overlap W	Entropy W
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Location revealed	-0.720***	-0.687***	-0.032***	-0.928***	-0.684***	-0.616***	-0.548***
	[0.123]	[0.130]	[0.005]	[0.149]	[0.137]	[0.130]	[0.138]
h-U-boat FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
h-day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.126	0.126	0.129	0.128	0.132	0.129	0.131
Mean dep var	0.785	0.782	0.035	1.123	1.055	1.016	1.092
Observations	474375	472758	474375	474375	474342	474342	474342

Notes: Unit of observation: U-boat day. Outcome is the number of ships sunk multiplied by 100, so magnitudes can be interpreted as percentage points. Column 1 is the baseline difference-in-differences regression to equation 2. Column 2 shows the estimate for location decrypts, that do not co-mention "convoy." Column 3 shows the baseline effect on the inverse hyperbolic sine of the number of sunk ships. Column 4 adds the number of sunk battleships to the outcome variable. Column 5 reweights the control group within twenty propensity score bins to attain balance in the number of treated and untreated observations. Column 6 uses overlap weights. Column 7 weights using entropy balance. Weights are based on $t-1$ covariates: patrol number, days on current patrol, the number of previous location revelations, messages without geoinformation, previously sunk merchant ships, commander experience in days, latitude, and longitude. Standard errors are clustered on U-boat-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D6: U-boat survival after five days.

	Baseline	- Conv. mentioned	P-score bin W	Overlap W	Entropy W
	(1)	(2)	(3)	(4)	(5)
Treatment at t+5	-0.011***	-0.009**	-0.013***	-0.010**	-0.009**
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
h-U-boat FE	Yes	Yes	Yes	Yes	Yes
h-day FE	Yes	Yes	Yes	Yes	Yes
R^2	0.424	0.424	0.437	0.435	0.437
Mean dep var at t+5	0.963	0.963	0.963	0.962	0.961
Observations	474375	472758	474342	474342	474342

Notes: Unit of observation: U-boat day. Outcome is U-boat survival. All columns show average survival differences five days after cohort treatment. Column 1 is the baseline specification. Column 2 shows the estimate for location decrypts, that do not co-mention "convoy". Column 3 reweights the control group within twenty propensity score bins to attain balance in the number of treated and untreated observations. Column 4 uses overlap weights. Column 5 weights using entropy balance. Weights are based on $t-1$ covariates: patrol number, days on current patrol, the number of previous location revelations, messages without geoinformation, previously sunk merchant ships, commander experience in days, latitude, and longitude. Standard errors are clustered on U-boat-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D7: Heterogeneity by ship type.

	Baseline	Large	Small	Ballast
	(1)	(2)	(3)	(4)
Location revealed	-0.720***	-0.345***	-0.375***	-0.167***
	[0.123]	[0.080]	[0.080]	[0.062]
h-U-boat FE	Yes	Yes	Yes	Yes
h-day FE	Yes	Yes	Yes	Yes
R^2	0.126	0.114	0.116	0.113
Mean dep var	0.785	0.401	0.383	0.201
Relative difference	-92%	-86%	-98%	-83%
Observations	474375	474375	474375	474375

Notes: Unit of observation: U-boat day. Outcome is the number of ships sunk multiplied by 100, so magnitudes can be interpreted as percentage points. Column 1 is the baseline difference-in-differences regression to equation 2. Column 2 shows the estimate for above-median-sized ships in terms of tonnage. Column 3 shows the estimate for below-median-sized ships in terms of tonnage. Column 4 shows the estimate for ships carrying ballast. Standard errors are clustered on U-boat-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D8: Correlation between patrolling units and sunk merchant ships.

	Sunk merchant ships			
	(1)	(2)	(3)	(4)
U-boats on patrol	0.015***	0.014***	0.019***	0.045***
	[0.002]	[0.003]	[0.006]	[0.013]
Ships on voyage (1000s)	-2.941***	-0.958***	0.148	0.274
	[0.149]	[0.365]	[0.497]	[1.155]
Day FE	No	Yes	Yes	Yes
Month FE	No	Yes	No	No
Year FE	No	Yes	No	No
Year-Month FE	No	No	Yes	Yes
R^2	0.136	0.214	0.291	0.232
Mean dep var	1.271	1.271	1.271	1.821
Sample	Full	Full	Full	No Enigma
Observations	2074	2074	2074	1014

Notes: Unit of observation: day. U-boats on patrol is the daily number of patrolling U-boats. Ships on voyage are the number of merchant vessels actively sailing in covoys in units of 1000s. Sample periods either September 1939 to May 1945 if "Full" indicated, or if "No Enigma" indicated, the periods in which U-boat Enigma codes were *not* broken: September 1939 to July 1941 and February 1942 to December 1942. Robust standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D9: Correlation between patrol experience and propensity to report position.

	Probability of position report (p.p.)				
	(1)	(2)	(3)	(4)	(5)
Commander experience (days)	-0.0004	0.0009	-0.0025*	-0.0003	-0.0031*
	[0.0012]	[0.0018]	[0.0015]	[0.0021]	[0.0016]
R^2	0.000	0.000	0.000	0.000	0.000
Mean dep var	3.103	2.430	3.615	2.537	3.622
Experience restriction	None	None	None	100+days	100+day
Commander capacity	All	Low	High	Low	High
Observations	67829	29265	38564	23772	34123

Notes: Unit of observation: U-boat-day. Commander experience is the cumulative number of days a commander has spent on patrol. The outcome is the probability of a U-boat sending a position report in percentage points. Column (1) covers the full sample. Columns (2) and (4) show estimates for below-median fixed effect commanders and columns (3) and (5) for above-median commanders. Columns (4) and (5) are further restricted to commanders who survive at least 100 days. Estimates are fit on experience above at least two weeks (which are typically spent en-route towards a first patrol position with very little communication). Standard errors are clustered by commander.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.1 Validation

To perform a simple validation exercise, I study differences in aggregate outcomes across different Axis powers focusing on the change in the information environment in December 1942. Empirically, I employ a canonical difference-in-differences design. The first difference is time, where I compare periods before and after the 14th of December 1942 when the Allies relearned how to read Enigma messages. The second difference I rely on are successes and losses by other Axis powers engaged in U-boat warfare, the Japanese and Italians. Importantly, the treatment status of the control groups did not switch around the event period. Italian submarines typically operated in radio silence, having been instructed before patrols. Hence, there was less scope to engage in decryption (Chadwick, 2011).[46] Japanese naval ciphers were instead regularly read starting from the 18th of March 1942 (Budiansky, 2000, p. 342). I then estimate the following equation

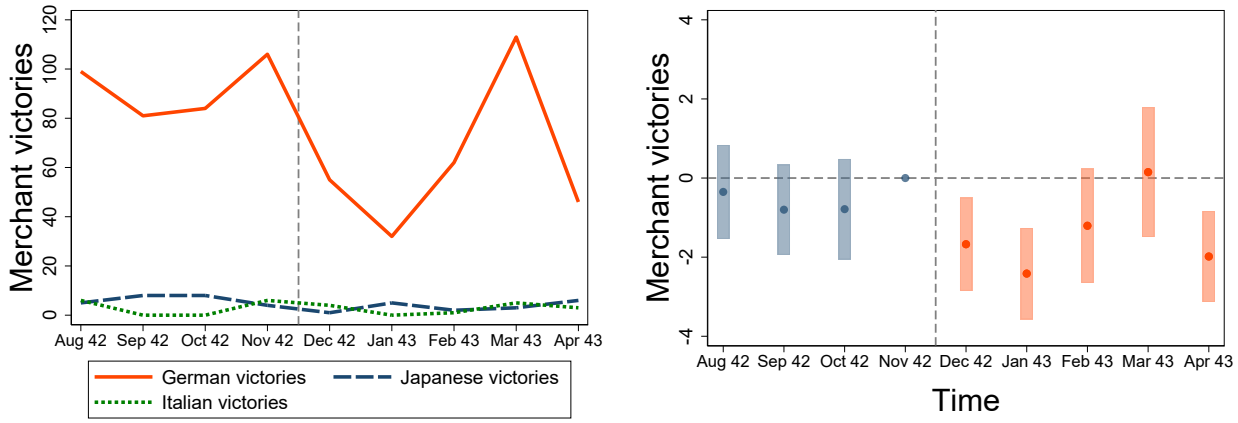
$$y_{it} = \beta Post_t \cdot Nazi_i + \alpha_i + \gamma_t + \varepsilon_t \tag{4}$$

where y_{it} are conflict outcomes on day t for Axis power i, $Post_t$ is an indicator that equals one for days after the 14th December 1942, $Nazi_i$ is an indicator for Nazi war outcomes. α_i captures Axis power fixed effects, since Germans sank many more convoys than the Japanese and Italians. Finally, γ_t are date fixed effects, and ε_t denotes the error term. Standard errors are clustered by date.

The corresponding event study estimates, binned by month to reduce noise, are shown in Figure D11. I find that roughly 0.8 fewer merchant ships per day are being sunk in the post-period (Appendix Table D10). This corresponds to a reduction of roughly 32 percent. I interpret the similarity in magnitude relative to the simulation result as evidence supporting the credibility of the quantification exercise.

[46] One disadvantage of this approach was that when an Italian submarine was captured, documents on board revealed patrolling orders of other submarines. For instance, the capture of the *Galileo Galilei* led to three subsequent submarine losses (Hinsley, 1979, p. 209).

Figure D11: Reading Enigma ciphers: zooming in on the 14th December 1942.



(a) Sunk merchant vessels (raw data)

(b) Sunk merchant vessels (event study)

Notes: The left-hand figure presents the number of sunk convoys per month and Axis power. The right-hand figure presents event study point estimates for the differences in merchant ships sunk by Germans versus Japanese and Italians. Lines indicate 95 percent confidence intervals. Standard errors are clustered by date.

Table D10: Static difference-in-differences: Effect on hit merchant vessels.

	Sunk merchant ships	
	(1)	(2)
German × Post	-0.796***	-0.796***
	[0.306]	[0.306]
German	2.763***	
	[0.189]	
Post	-0.050*	
	[0.028]	
Axis power FE	No	Yes
Date FE	No	Yes
Cons.	Yes	No
R^2	0.370	0.585
German Mean	2.484	2.484
N Clusters	273	273
Observations	819	819

Notes: Unit of observation: axis-day. Estimates of Equation 4. Sample period August 1942 to April 1943. Standard errors clustered by date.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Adena, Maja, Ruben Enikolopov, Maria Petrova, and Hans-Joachim Voth. 2021. "Bombs, Broadcasts and Resistance: Allied Intervention and Domestic Opposition to the Nazi Regime during World War II." *Available at SSRN 3661643*. ↩ 6

Ager, Philipp, Leonardo Bursztyn, Lukas Leucht, and Hans-Joachim Voth. 2022. "Killer Incentives: Rivalry, Performance and Risk-Taking Among German Fighter Pilots, 1939–45." *Review of Economic Studies*, 89(5): 2257–2292. ↩ 6

Axelrod, Robert. 1979. "The Rational Timing of Surprise." *World Politics*, 31(2): 228–246. ↩ 10

Barlow, Jeffrey G. 2008. "The Navy's Atlantic War Learning Curve." *Naval History*, 22(3): 22. ↩ 32

Batey, Mavis. 2011. "Breaking Italian Naval Enigma." In *The Bletchley Park Codebreakers: How Ultra Shortened the War and Led to the Birth of the Computer*. , ed. Ralph Erskine and Michael Smith. Biteback Publishing. ↩ 9

Beesly, Patrick. 1977. *Very Special Intelligence.* Greenhill Books (2000). ↩ 2, 7, 8, 9, and 15

Beesly, Patrick. 1990. "Convoy PQ 17: A Study of Intelligence and Decision-Making." *Intelligence and National Security*, 5(2): 292–322. ↩ 13

Bennett, Ralph. 1996. "Intelligence and Strategy: Some Observations on the War in the Mediterranean 1941–45." In *Intelligence Investigations: How Ultra Changed History*. Chapter 5. Frank Cass Co. Ltd. ↩ 10

Budiansky, Stephen. 2000. *Battle of Wits.* Simon and Schuster. ↩ 7, 15, 21, 52, and 84

Caselli, Francesco, Massimo Morelli, and Dominic Rohner. 2015. "The Geography of Interstate Resource Wars." *The Quarterly Journal of Economics*, 130(1): 267–315. ↩ 1 and 5

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-Wage Jobs." *The Quarterly Journal of Economics*, 134(3): 1405–1454. ↩ 24

Chadwick, John. 2011. "A Biographical Fragment: 1942–5." In *The Bletchley Park Codebreakers: How Ultra Shortened the War and Led to the Birth of the Computer*. , ed. Ralph Erskine and Michael Smith. Biteback Publishing. ↩ 84

Churchill, Winston. 1952. *The Second World War. Closing the Ring*. Vol. 5, Cassell. ↩ 8

Conconi, Paola, Nicolas Sahuguet, and Maurizio Zanardi. 2014. "Democratic Peace and Electoral Accountability." *Journal of the European Economic Association*, 12(4): 997–1028. ↩ 5

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review*, 110(9): 2964–2996. ↩ 24

Dönitz, Karl. 1958. *Memoirs Ten Years and Twenty Days.* ↩ 10

Eichengreen, Barry, Massimo Ferrari Minesso, Arnaud Mehl, Isabel Vansteenkiste, and Roger Vicquéry. 2024. "Sanctions and the exchange rate in time." *Economic Policy*, 39(118): 323–354. ↩ 77

Einzig, Paul. 1970. *The History of Foreign Exchange.* . 2nd ed., London and Basingstoke:The Macmillan Press Ltd. Revised and enlarged edition. First edition 1962. Reprinted with alterations 1964. Reprinted 1979. ↩ 31

Erskine, Ralph. 1988. "Naval Enigma: The Breaking of Heimisch and Triton." *Intelligence and National Security*, 3(1): 162–183. ↩ 3, 20, and 21

Erskine, Ralph. 1989. "Naval Enigma: A Missing Link." *International Journal of Intelligence and Counter Intelligence*, 3(4): 493–508. ↩ 7

Erskine, Ralph. 1992. "The German Naval Grid in World War II." *Cryptologia*, 16(1): 39–51. ↩ 8

Erskine, Ralph, and Frode Weierud. 1987. "Naval Enigma: M4 and its Rotors." *Cryptologia*, 11(4): 235–244. ↩ 10

Erskine, Ralph, and Philip Marks. 2004. "Naval Enigma: Seahorse and Other Kriegsmarine Cipher Blunders." *Cryptologia*, 28(3): 211–241. ↩ 20 and 63

Federle, Jonathan, Dominic Rohner, and Moritz Schularick. 2024. "Who Wins Wars?" *Available at SSRN 5093393*. ↩ 5

Fetzer, Thiemo, Pedro CL Souza, Oliver Vanden Eynde, and Austin L Wright. 2021. "Security Transitions." *American Economic Review*, 111(7): 2275–2308. ↩ 5

Flanders Marine Institute. 2018. *IHO Sea Areas, Version 3.* Available online at https://www.marineregions.org/, https://doi.org/10.14284/323 (accessed September 22nd, 2022). ↩ 63

Flanders Marine Institute. 2021. *Global Oceans and Seas, Version 1.* Available online at https://www.marineregions.org/, https://doi.org/10.14284/542 (accessed September 22nd, 2022). ↩ 63

Glitz, Albrecht, and Erik Meyersson. 2020. "Industrial Espionage and Productivity." *American Economic Review*, 110(4): 1055–1103. ↩ 6

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277. ↩ 24

Gröner, Erich. 1990. *German Warships, 1815-1945: U-Boats and Mine Warfare Vessels.* Vol. 2, Naval Institute Press. ↩ 42

Guglielmo, Mark. 2008. "The Contribution of Economists to Military Intelligence during World War II." *The Journal of Economic History*, 68(1): 109–150. ↩ 6

Hague, Arnold. 2000. *The Allied Convoy System 1939–1945: Its Organization, Defence and Operation.* Vanwell. ↩ 14

Hainmueller, Jens. 2012. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies." *Political Analysis*, 20(1): 25–46. ↩ 28

Hess, Gregory D, and Athanasios Orphanides. 1995. "War Politics: An Economic, Rational-Voter Framework." *American Economic Review*, 85(4): 828–846. ↩ 5

Hileman, Garrick. 2017. "Currency black markets and historical turning points: ‚ÄòFree‚Äô sterling in new york and switzerland in the 1940s." *Working Paper*. ↩ 77

Hinsley, Francis Harry. 1979. *British Intelligence in the Second World War.* Vol. 1, Cambridge University Press. ↩ 84

Hinsley, Francis Harry. 1981. *British Intelligence in the Second World War.* Vol. 2, Cambridge University Press. ↩ 7

Hinsley, Francis Harry. 1984. *British Intelligence in the Second World War.* Vol. 3, Part I, Cambridge University Press. ↩ 63

Hinsley, Fred H. 1990. "British Intelligence in the Second World War: An Overview." *Cryptologia*, 14(1): 1–10. ↩ 9

Imbens, Guido W, and Donald B Rubin. 2015. *Causal Inference in Statistics, Social, and Biomedical Sciences.* Cambridge University Press. ↩ 25 and 28

Jackson, Matthew O, and Stephen Nei. 2015. "Networks of Military Alliances, Wars, and International Trade." *Proceedings of the National Academy of Sciences*, 112(50): 15277–15284. ↩ 5

Kahn, David. 1991. *Seizing the Enigma: The Race to Break the German U-boat Codes, 1939-1943.* ↩ 7, 30, and 40

Knowles, Kenneth. 1977. "Ultra and the Battle of the Atlantic: The American View." U.S. Naval Academy in Annapolis on October 28, 1977. ↩ 9, 30, and 32

Kohnen, David. 1999. *Commanders Winn and Knowles: Winning the U-boat War with Intelligence, 1939-1943.* Enigma Press. ↩ 8, 9, 32, and 33

Kohnen, David. 2019. "The Cruise of U-188: Special Intelligence and the "Liquidation" of Group Monsoon, 1943–1944." In *Decision in the Atlantic: The Allies and the Longest Campaign of the Second World War*. , ed. Marcus Faulkner and Christopher M. Bell, Chapter 10. University Press of Kentucky. ↩ 9, 20, 29, and 33

Li, Fan, Laine E Thomas, and Fan Li. 2019. "Addressing Extreme Propensity Scores via the Overlap Weights." *American Journal of Epidemiology*, 188(1): 250–257. ↩ 28

Martin, Philippe, Thierry Mayer, and Mathias Thoenig. 2008. "Make Trade not War?" *Review of Economic Studies*, 75(3): 865–900. ↩ 1 and 5

Mulligan, Timothy P. 1985. "The German Navy Evaluates Its Cryptographic Security, October 1941." *Military Affairs*, 49(2): 75–79. ↩ 42

Naval History Division. 1963. *United States Submarine Losses in World War II.* Washington, D.C. [Revised 2017]. ↩ 63

Rapping, Leonard. 1965. "Learning and World War II Production Functions." *Review of Economics and Statistics*, 81–86. ↩ 42

Ratcliff, Rebecca A. 1999. "Searching for Security: The German Investigations into Enigma's Security." In *Allied and Axis Signals Intelligence in World War II.* , ed. David Alvarez, 146–167. Frank Cass. ↩ 10, 42, and 43

Rexer, Jonah M. 2025. "Corruption as a Local Advantage: Evidence from the Indigenization of Nigerian Oil." *American Economic Review*, 115(3): 1019–57. ↩ 24

Rohwer, Jürgen. 1979. *Die Funkaufklärung und ihre Rolle im Zweiten Weltkrieg: e. internat. Tagung in Bonn-Bad Godesberg u. Stuttgart vom 15.-18. November 1978.* Motorbuch-Verlag. ↩ 19, 20, and 21

Rohwer, Jürgen. 1988. *Allied and Axis Radio-Intelligence in the Battle of the Atlantic: A Comparative Analysis.* ↩ 20

Rohwer, Jürgen. 1999. "Axis Submarine Successes of World War Two: German, Italian and Japanese Submarine Successes, 1939-1945." ↩ 9, 13, and 63

Rohwer, Jürgen, and Gerhard Hümmelchen. 2005. *Chronology of the War at Sea, 1939-1945: The Naval History of World War Two.* Chatham. 3rd Revised Edition. ↩ 14

Rozenas, Arturas, Roya Talibova, and Yuri M Zhukov. 2024. "Fighting for tyranny: State repression and combat motivation." *American Economic Journal: Applied Economics*, 16(3): 44–75. ↩ 6

Sebag-Montefiore, Hugh. 2000. "Enigma: The Battle for the Code." ↩ 7 and 52

SIPRI. 2025. "Trends in World Military Expenditure, 2024." Stockholm International Peace Research Institute (SIPRI) SIPRI Fact Sheet. ↩ 1

Smith, Christopher. 2021. "Bletchley Park and Big Science: Industrialising the Secret War, 1939-1945." *Journal of Intelligence History*, 20(2): 109–125. ↩ 5 and 41

Sonin, Konstantin, and Austin L Wright. 2024. "Rebel Capacity, Intelligence Gathering, and Combat Tactics." *American Journal of Political Science*, 68(2): 459–477. ↩ 5

Spolaore, Enrico, and Romain Wacziarg. 2016. "War and Relatedness." *Review of Economics and Statistics*, 98(5): 925–939. ↩ 5

Syrett, David. 1998. *The Battle of the Atlantic and Signals Intelligence: U–Boat Situations and Trends, 1941–1945.* Ashgate. ↩ 18 and 29

Syrett, David. 1999. "Communications Intelligence and the Sinking of the U-860, April-June 1944." *The Mariner's Mirror*, 85(1): 68–75. ↩ 7, 8, 23, and 43

Syrett, David. 2002. "The Infrastructure of Communications Intelligence: The Allied D/F Network and the Battle of the Atlantic." *Intelligence and National Security*, 17(3): 163–172. ↩ 8

Thompson, Peter. 2001. "How Much Did the Liberty Shipbuilders Learn? New Evidence for an Old Case Study." *Journal of Political Economy*, 109(1): 103–137. ↩ 42

Thornton, Rebecca Achee, and Peter Thompson. 2001. "Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding." *American Economic Review*, 91(5): 1350–1368. ↩ 42

US Congress. 2024. "Intelligence Community Spending Trends." Congressional Research Service R44381. ↩ 1

Wallis, W Allen. 1980. "The Statistical Research Group, 1942–1945." *Journal of the American Statistical Association*, 75(370): 320–330. ↩ 6

Walters, Christopher. 2024. "Empirical Bayes methods in labor economics." In *Handbook of Labor Economics*. Vol. 5, 183–260. Elsevier. ↩ 30

Williams, Greg H. 2014. *The Liberty Ships of World War II: A Record of the 2,710 Vessels and Their Builders, Operators and Namesakes, with a History of the Jeremiah O'Brien.* McFarland. ↩ 5, 40, and 42

Wintrobe, Ronald. 1998. *The Political Economy of Dictatorship.* Cambridge University Press. ↩ 43

Wright, John. 2017. "The Turing Bombe Victory and the First Naval Enigma Decrypts." *Cryptologia*, 41(4): 295–328. ↩ 3 and 21

Wu, Yuxin, Alexander Kirillov, Francisco Massa, Wan-Yen Lo, and Ross Girshick. 2019. "Detectron2." https://github.com/facebookresearch/detectron2. ↩ 64