

El Niño amplified food insecurity in early modern Europe

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The El Niño–Southern Oscillation (ENSO) is a dominant source of global inter-annual climate variability. Yet its influence on food security during the early modern period remains comparatively underexplored. Drawing on a recently compiled dataset of 160 European famine episodes and a new high-resolution ENSO reconstruction, we show a robust correspondence between positive ENSO anomalies (El Niño events) and subsistence crises during the early modern period (1500–1800). These anomalies increased the probability of famine onset in Central Europe – the European region that we find most teleconnected with ENSO variability – where we estimate that more than 40% of famine onsets are associated with El Niño events. To explain this finding, we establish a pathway in which positive ENSO anomalies are revealed (1) to be associated with excessive summer wetness and (2) consequently reduced grain harvests. We further show that ENSO effects on famine duration were even more widespread: El Niño events increased the annual likelihood of famine persistence by 24% in all nine European regions for which data are available. To explain this finding, we study grain price data and show that ENSO-induced climate variability drove grain prices up by 6.5% after one year – even in non-teleconnected locations. We posit that this outcome is consistent with significant market integration that allowed climate-related shocks to propagate across the continent. We further show that these grain price shocks spilled over to other subsistence goods, such as fish, an effect we attribute to demand substitution given the lack of apparent ENSO influence on European and North Atlantic marine environments. Collectively, these results provide new evidence for the influence of mechanisms of global climate variability on regional food security during the early modern period in Europe.

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1 Introduction

Early modern Europe (c. 1500–1800) experienced large-scale political, socio-economic, and cultural transformations[1] that occurred in tandem with the climatic cooling of the Little Ice Age[2, 3, 4]. During the late 16th century and throughout much of the 17th century in particular, many parts of Europe endured repeated famines[5, 6, 7]. These subsistence crises occurred despite advances in agriculture and food trade networks that should (in theory) have bolstered food security[8], although frequent large-scale wars likely weakened the effects of this progress (see Parker [9]). While social and political events, not least warfare, can credibly explain some of these famines, it is clear that consecutive years of adverse climatic conditions for agriculture also played an important role for famine causation in strongly grain-dependent pre-industrial Europe[10, 11]. Cold and late springs followed by excessively wet and cold summers constituted the major climatic threat to food production in Northern and Central Europe, whereas droughts posed a relatively greater threat in the Mediterranean region[2, 11, 12]. While the proximate meteorological conditions triggering historic European famines have been documented[5], there is a significant knowledge gap on the ultimate causal role of global-scale modes of climatic variability on the onset and duration of these famine episodes. The role of the El Niño–Southern Oscillation (ENSO) has been particularly overlooked in analyses of European food security and famine history.

ENSO is a primary driver of global inter-annual climate variability, with profound effects on weather patterns that influence socio-economic conditions across diverse regions globally[13, 14]. Its contemporary impacts have been extensively studied in tropical and subtropical regions, where it modulates precipitation and temperature patterns, promoting droughts, floods, and other extreme weather events[15, 16]. These events have significantly affected economies[17], agriculture and food security[18, 19, 20, 21], and potentially increased civil conflict probability[22]. ENSO effects on temperature and precipitation patterns are particularly pronounced in large parts of Africa, Australia, North and South America, but its influence also extends globally through long-distance climatic “teleconnections” [23] (significant links between weather phenomena at widely separated locations on Earth)[24]. For Europe, the contemporary influence of ENSO on precipitation is subject to ongoing study[25]. Notably, studies have established teleconnections between ENSO and spring–summer excess rainfall [26, 27, 28]. The influence of ENSO teleconnections on pre-industrial European climate remains, however, under-explored.

The effects of ENSO on pre-industrial food security also remain understudied, despite dramatic examples of how particular historical El Niño events disrupted harvests. For instance, the El Niño anomaly of 1788–1793 weakened monsoon rainfall in India, promoting widespread crop failures and triggering a series of notable and far-reaching societal disruptions across multiple world regions, including conjectured links to the French Revolution (1789)[29, 30]. Qualitative studies have also documented links between extreme El Niño events and catastrophic 19th-century famines in South Asia, East Asia, and South America, while also

highlighting the mediating role of governance failures and exploitative trade systems that restricted access to locally grown grain by the poor[21]. The late 19th-century “Great Drought” (1875–1878), associated with a sequence of extreme oceanic temperature anomalies including a record-breaking El Niño, triggered a global famine with tens of millions of fatalities [31], underscoring the potential for ENSO-related climate variability to generate synchronized, multi-year food crises across continents.

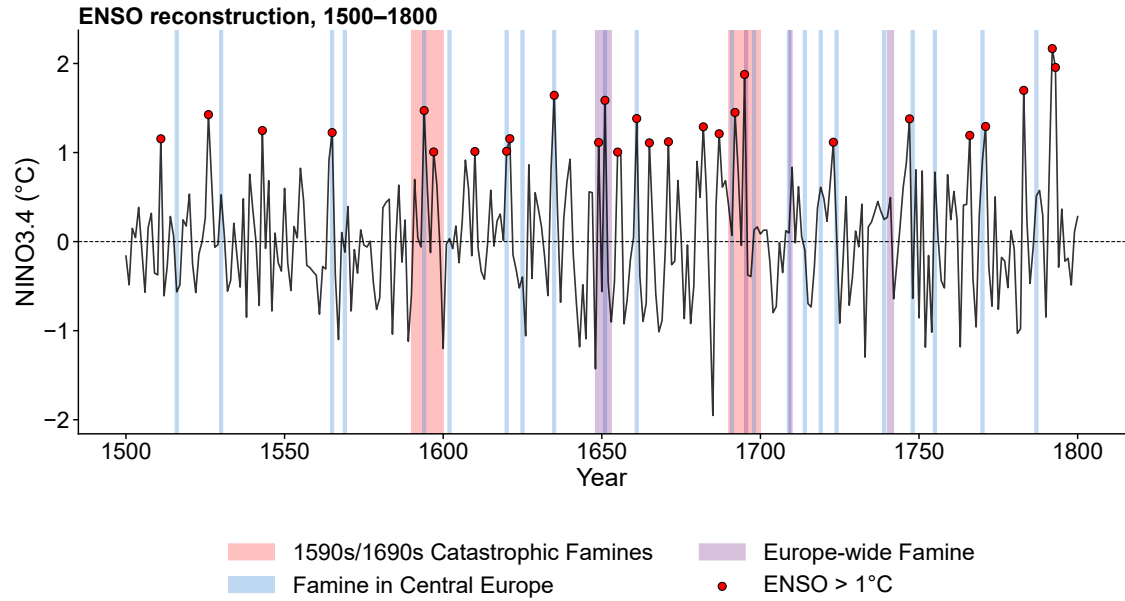
This study presents novel quantitative evidence of ENSO impacts on food security in early modern Europe. Using extensive data compiled by historians since the late 19th century, we demonstrate that positive ENSO anomalies (including major El Niño events) increased the probability of famine onsets in Central Europe, where we estimate it contributed to the onset of over 40% of the famine episodes, whereas elsewhere in Europe the influence of ENSO can be seen in extending the duration of existing famines. To explain these findings, we establish a plausible causal pathway along which ENSO impacted food security. Specifically, we show that ENSO variability can be detected in (1) European soil moisture and precipitation patterns, (2) grain harvests and, ultimately, (3) grain and fish prices.

Research on the early modern climate–food security nexus has focused primarily on grain harvests and trade, often overlooking other climate-sensitive components of the food system, such as marine food sources, which have been historically integral to subsistence and trade[32]. Thus, we also explore the effects of ENSO on fish prices and observe a notable response that suggests a demand-side substitution effect on fish prices driven by terrestrial crop failures, rather than a supply-side response in which fish prices are driven by catch variation under the influence of ENSO. By delineating these pathways of effect, we advance understandings of how global-scale modes of climate variability shaped food systems and livelihoods in early modern Europe.

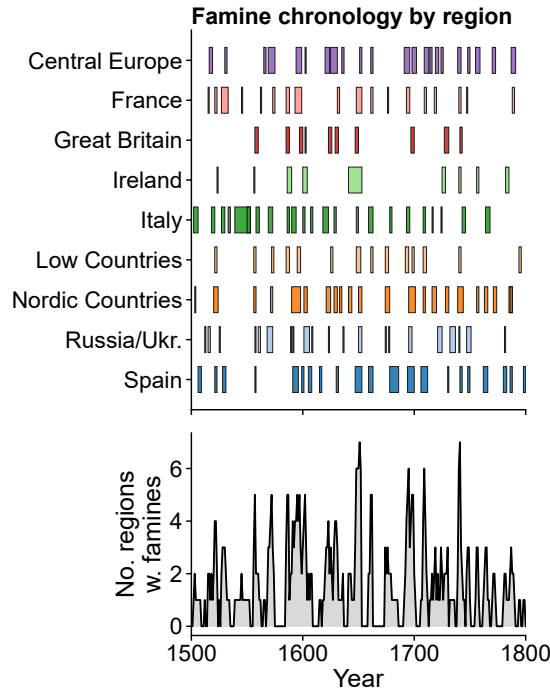
2 Results

To examine the role of ENSO in early modern European subsistence crises, we treat it as an exogenous and unpredictable source of short-term climate fluctuations. Rather than confine our attention to severe El Niño events with a pre-determined threshold, we focus on how continuous and plausibly random ENSO variability influenced European climate, harvests, and prices, thereby contributing to subsistence crises. For this, we use a novel tree-ring-based reconstruction of sea surface temperatures across the equatorial Pacific by Cook and Cane [33] during the boreal winter (December–February) season, when ENSO influence on the global climate is strongest. There is a strong correlation between ENSO conditions in the preceding summer and autumn, the following early spring, and those during December–February. From this reconstruction, we capture ENSO by deriving the NINO3.4 index, defined as the average sea surface temperature (SST) anomaly in region 5°N–5°S, 170°W–120°W, relative to a 1801–1900 reference period. NINO3.4 is the most widely used proxy for identifying El Niño conditions, conventionally defined as positive SST anomalies that lie above a

a



b



c

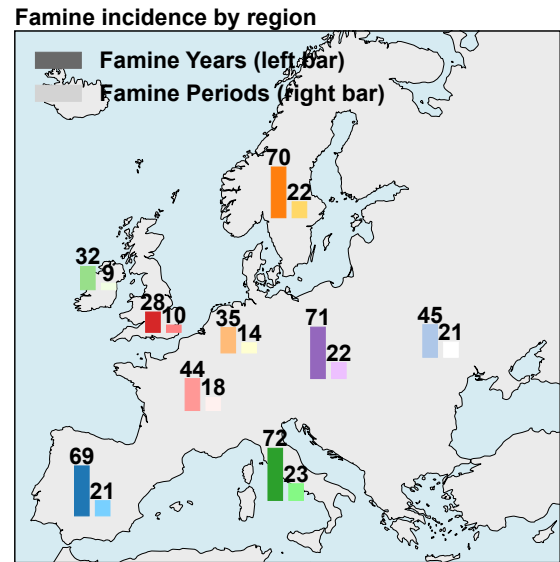


Figure 1: ENSO and famines in Early Modern Europe. (A) ENSO index (NINO3.4 Region boreal winter SST anomalies relative to the 1801–1900 mean), with extreme values (red dots $\geq 1^\circ\text{C}$) linked to key societal crises (pink: 1590s and 1690s Catastrophic Famines; blue: Famines in Central Europe; purple: 1647–1652 Europe-wide Famines). (B) The top panel presents famine periods across different regions. Each horizontal bar represents a continuous famine episode within a given region, spanning from the estimated onset year to its termination. The bottom panel shows the annual number of concurrent famine years aggregated across all regions. (C) Map of all nine regions covered by the Ljungqvist et al. [7] famine data. Number of famine periods (right bars) and total years spent in famines (left bars) within each region (bars located in the center of each region).

given threshold. In our analysis, we use “El Niño” and “positive ENSO anomalies” interchangeably, while noting that the standard threshold-based definition may be less relevant in a long-term historical context.

We first pair this ENSO reconstruction with a compilation of famine years across nine European regions published in Ljungqvist et al. [7]. Figure 1 highlights the main variables of interest by depicting famine onset (timing) and duration in relation to ENSO anomalies. Initial visual inspection suggests that peak El Niño events closely coincided with many famine periods.

2.1 ENSO Linked to the Onset of Famine Periods in Teleconnected Regions

More formally, we find that El Niño events were statistically significantly associated with famine onsets in Central Europe (Figure 2A,B), where we estimate that a $+1^{\circ}\text{C}$ ENSO anomaly was associated with an average 6.9 percentage point (95% confidence interval [CI]: [1.7, 12.0]) increase in the probability of a famine onset for that year (i.e., increasing from 6.9% in neutral conditions to 13.9% with a 1°C anomaly). We derive our estimate from a linear probability model with region and decade fixed effects that isolates the plausibly causal impact of ENSO, removing the influence of region and decade-specific unobservables. This approach, motivated by the recent climate impacts literature (see [34] for a review), rests on the assumption that year-to-year climate variability is “as good as randomly assigned” once decade- and region-specific factors are removed—an assumption particularly well justified for ENSO, whose onset remains irregular at inter-annual scales [35]. This assumption entails that ENSO realizations are independent of potential confounders of famine onset. As a result, concerns about confounding are substantially mitigated, and differences in outcomes across ENSO realizations can be interpreted as identifying the causal effect of ENSO. We also note that a 1°C anomaly lies near the upper 90th percentile of our annual NINO3.4 values, and thereby offers a meaningful measure of extreme El Niño events without leaning on extrapolation.

Our estimate remains largely unchanged when controlling for other potential influences on famine onset, namely European conflict severity and, crucially, other large-scale drivers that might act as potential confounders, such as the North-Atlantic Oscillation (NAO), known to influence present-day European agriculture [36], or the European Jet Stream Latitude (JSL). More specifically, we extend our model to condition on the annual number of ongoing wars and conflict-related fatalities from the Conflict Catalog [37], which provides a comprehensive record of armed conflicts since antiquity, while we employ the annually resolved NAO reconstruction of Ortega et al. [38] (calibrated reconstruction) and the annual Jet Stream Latitude index of Xu et al. [39].

Despite the strong association between ENSO and famine onset for Central Europe, we do not find any statistically significant association for other specific regions or for Europe on average (see a full regression table in Extended Data Table 1). To further assess whether the observed association for Central Europe is

spurious, we therefore use a falsification approach (Supplementary S9.3) in which we replace the observed ENSO values with fully randomized, false ENSO histories. No systematic relationship with famine onsets in Central Europe emerges: only 0.2% of our 1,000 false histories yield an equally or more extreme estimate, ruling out a spurious correlation with Central European famine onsets.

Machine Learning Attribution of ENSO-related Famines We next aim to identify which Central European famines were triggered by ENSO conditions. Our fixed-effects regression framework (above), while establishing robust associations between ENSO and famine onsets, is able to predict only one of the 22 historical famine events in-sample. This limited predictive power diminishes its usefulness for robust attribution. To address this gap, and in line with calls to integrate causal inference with predictive approaches [40], we employ a machine learning classifier (see Methods 4.2). The model conditions on ENSO alongside other historically relevant covariates to classify each year as a famine onset or not. Specifically, we use the yearly number of ongoing wars and conflict-related fatalities from the Conflict Catalog [37], which provides a comprehensive record of armed conflicts since antiquity; seasonal temperature and precipitation (November–February and April–July) from the ModeE-RA reanalysis [41], a global state-of-the-art reanalysis of monthly climate variables; and June–August soil moisture from the Old World Drought Atlas [42], a tree-ring-based reconstruction of the self-calibrating Palmer Drought Severity Index (scPDSI), used to infer past hydroclimate variability in Europe. The classifier not only perfectly predicts famine onsets in-sample (100% accuracy) but also maintains high accuracy under cross-validation (Figure 2E), supporting its relevance for attribution. We note that the cross-validated out-of-sample performance is affected by class imbalance, which is inherent to the rarity of famine onset events in the historical record. While this limits predictive performance in a strict forecasting sense, our primary objective is not prediction into the future but attribution. In this context, the model’s ability to recover meaningful in-sample relationships is more relevant than its extrapolation performance.

We next leverage the model to perform a counterfactual simulation, allowing us to directly quantify the contribution of ENSO to historical famines in Central Europe. Specifically, by comparing the famine onsets under the observed ENSO conditions with counterfactual famine onsets under a scenario in which positive ENSO anomalies during such onset years are manually set to neutral (Figure 2C), we can identify which famines are attributable to ENSO variability. This counterfactual analysis suggests that nine of the 22 recorded famine periods in Central Europe for the study period can be directly linked to ENSO variability, representing over 40% of the famines for the period. This shows that while El Niño events were certainly not the sole cause, just under half of recorded famine events were associated with (at least partially triggered by) ENSO.

To assess the sensitivity of our estimate to different predictor choices, we re-tune the algorithm on restricted predictor sets. Across these specifications, the estimated attribution of El Niño ranges from five to nine famine onsets, corresponding to 23–40% of all observed Central European famine events (Supplementary

S3). The feature importance scores (Figure 2D), used to estimate which predictors were the most influential in the model’s predictions, highlight ENSO and June–August soil moisture (scPDSI) as the most important predictors, confirming ENSO’s importance in predicting onsets accurately and pointing to possible soil-moisture teleconnections.

Impact of ENSO on European climate and grain harvests While ENSO’s contemporary global climatic impacts are well-documented [43][44][45], its historical association with European hydroclimate (precipitation and soil moisture) is comparatively underexplored. A study by Baek et al. [46] finds strong coherence between reconstructed ENSO teleconnections and those observed in instrumental data, although tree-ring records appear to underestimate the wet conditions induced by El Niño events in Central Europe.

We identify potential teleconnections by correlating (Pearson’s r) the ENSO time-series with grid-point-level time series of April–July precipitation and scPDSI (data described earlier). These analyses reveal that positive ENSO anomalies were associated higher June–August soil moisture, and higher April–July precipitation (see Supplementary S4) in many European regions. Notably, however, we observe the strongest correlations (statistically significant at the 10% level) between positive ENSO anomalies and anomalously wet conditions in Central Europe and the Balkans (see Fig. 3A). We also observe this general pattern when comparing the average soil moisture during our 9 identified ENSO-triggered famines against all other years (Fig 3B).

The areas of strongest ENSO influence on European hydroclimate thus closely match the Central European region where famine onsets were statistically significantly associated with ENSO. This is consistent with studies that link ENSO to excess spring rainfall in Central Europe in the modern era [26, 27]. This correspondence suggests that excessively wet early summers were particularly disruptive to food security in Central Europe. Many studies [12, 10, 2, 3, 47] have documented the adverse effect of wet spring–summers, often combined with cold winters, on harvest outcomes in this region. Importantly, Baek et al. [48] also document a strong mode of European hydroclimate variability that is associated with the 1315–1317 Great Famine, during which soil moisture was excessively high in Western and parts of Central Europe. Our findings suggest the existence of an active causal pathway where ENSO teleconnections in Central Europe repeatedly produced adverse weather that depressed grain harvests to levels capable of triggering famines, given the prevailing socioeconomic context (including food access characteristics, and storage and distribution capabilities) of early modern Central Europe.

To further establish this, we assess the dynamic causal effects of ENSO anomalies on grain harvests. Our primary focus is on rye and wheat, with a secondary focus on other grains. As the two primary bread grains in much of Europe [11], and the most susceptible to damage from excessive wetness [2], rye and wheat were the main price-driving crops, making them particularly relevant to our analysis. Our extensive compilation of harvest data includes tithes (a percentage tax based on the annual harvest), yield ratio records

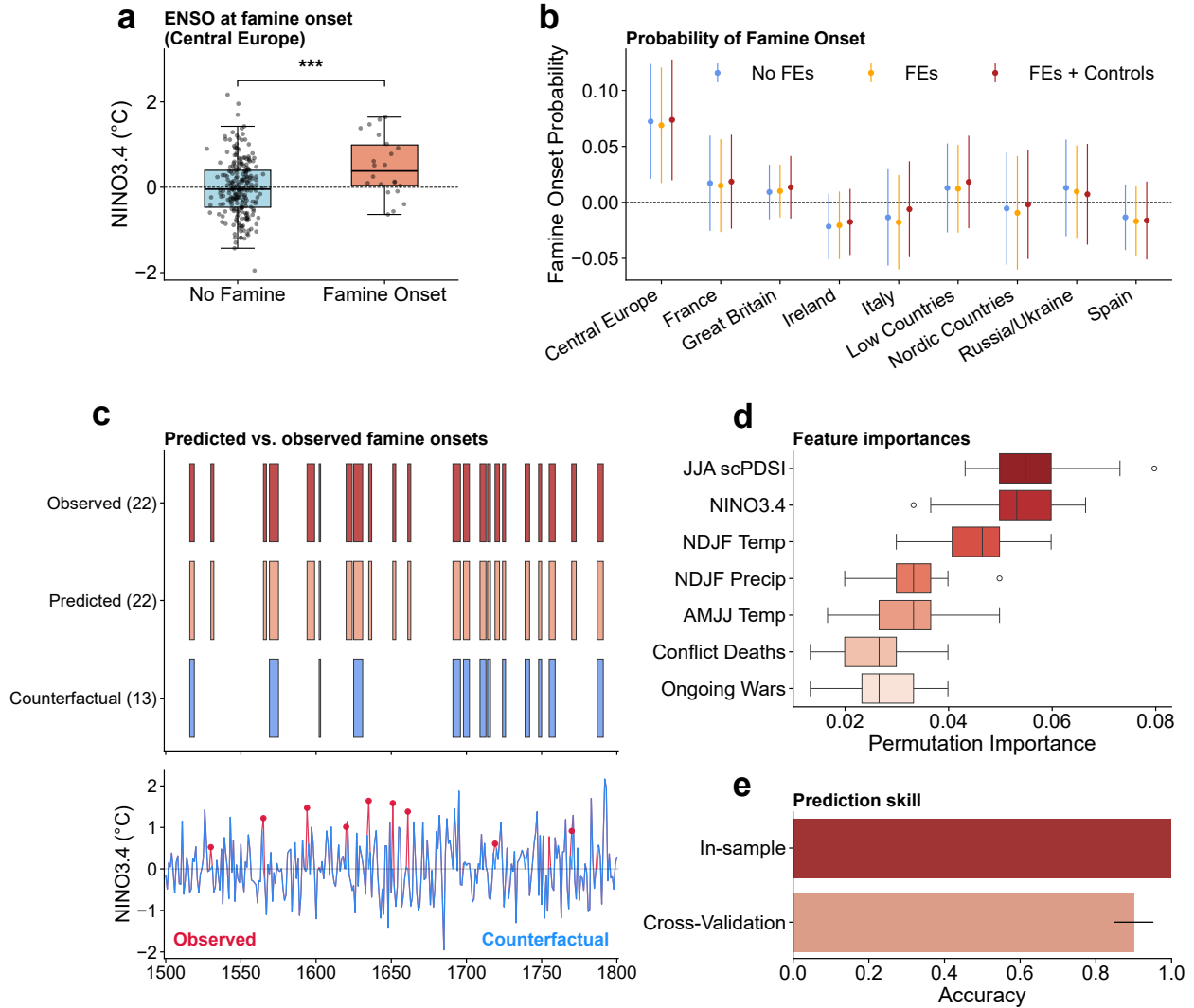


Figure 2: ENSO and the onset of famine periods. (A) Distribution of ENSO (NINO3.4) anomalies (annual values relative to the 1500–1800 mean) at famine onset in Central Europe. *** ($p < 0.01$) denotes statistical significance at the 1% level (two-sided t -test for differences in means). (B) Estimated effect of a +1 °C ENSO (NINO3.4) anomaly on the probability of famine onset, using a Linear Probability Model (LPM) with region-specific impacts. Yellow whiskers include Fixed-Effects (FEs), whereas red whiskers include FEs and the following controls: annual count of conflict-related deaths and ongoing wars, Jet Stream Latitude index (JSL) and North Atlantic Oscillation index (NAO). 95% confidence intervals with robust standard errors: Newey–West for models without FEs and Driscoll–Kraay for those with FEs. (C) Predicted, observed, and counterfactual chronologies of central European famine onsets from the Gradient Boosting classifier fine-tuned via a grid search performed via 10-fold cross-validation. The counterfactual represents a scenario in which positive ENSO anomalies are held at neutral conditions (NINO3.4 = 0) during historical onset years. (D) Permutation importance of the tuned Gradient Boosting classifier used to classify years into famine onsets, based on $N = 50$ permutations. Predictors include ENSO (NINO3.4), June–August (JJA) scPDSI, November–February (NDJF) temperature and precipitation, April–July (AMJJ) temperature, the annual number of ongoing conflicts and estimated conflict-related deaths. (E) Model performance in famine onset attribution. The cross-validation score reflects the mean accuracy across 10 folds.

(the proportion of yield in relation to seed) and some records of yield per unit[47]. All these harvest records reflect year to year harvest variations. We estimate impulse response functions to a $+1^{\circ}\text{C}$ ENSO shock on harvest data using panel local projections [49], which flexibly incorporate fixed effects for decade, location, and grain type to account for unobserved drivers in harvests fluctuations. Our impulse response functions thus isolate the contribution of a positive ENSO shock to inter-annual harvest variations, holding all other sources of variability constant, and allow us to determine the direction (or sign), magnitude, and temporal persistence of harvest responses.

Based on the consistency of observed teleconnections between ENSO and soil moisture (measured via the June–August scPDSI[42]), we also partition our harvest time-series into ‘Teleconnected’ and ‘Weakly affected’ groups. In teleconnected regions, rye and wheat harvests declined by an average of 6.2% (CI [1.4%, 11.1%]) following a $+1^{\circ}\text{C}$ ENSO shock (Figure 3A). . Although the observed responses are statistically significant, the estimates carry large standard errors, reflecting both the limited number of apparently teleconnected regions with available harvest records and their geographical clustering[47]. We also find that other grains types, including barley and oats, which are more resilient to wet conditions[2], showed weaker responses to positive ENSO shocks in teleconnected regions than rye and wheat, further confirming the important role of soil moisture teleconnections (Figure 3D).

We observe similar responses when we modulate our partition of the available harvest data by region (Central Europe *vs.* Rest of Europe; see Extended Data Figure 2), or when we partition based on observed ENSO teleconnections to April–July precipitation anomalies (see Supplementary S5). Our findings on grain harvests remain robust to alternative model specifications for capturing the persistent effects of ENSO shocks (Supplementary S9.1). Placebo ENSO shocks that use fully randomized ENSO histories produce no detectable harvest response, with estimates tightly centered around zero, while our baseline effects lie well outside the resulting null distributions (Supplementary S9.3). Using the yield ratio compilation from Slicher van Bath [50], as alternative harvest data, we obtain an even larger effect, presumably because a higher proportion of this (smaller) dataset derives from Central Europe (Supplementary S9.2). Finally, we confirm that our statistical inferences are not biased by spatial or temporal autocorrelations (Supplementary S9.6).

2.2 ENSO Prolonged Famines Across all European Regions

Beyond the dates of famine onset, famine duration is of great interest in influencing the scale of mortality and other impacts such as mass population displacement. We find that ENSO is associated with the duration of early modern European famines, across all nine regions in our compilation. Using a time-dependent Cox proportional hazards model stratified by region, we estimate that, on average across all nine regions, a $+1^{\circ}\text{C}$ ENSO anomaly occurring during an already ongoing famine reduced its likelihood (technically, instantaneous hazard) of ending by approximately 24% (hazard ratio = 0.76, CI [0.58, 0.99]), relative to the

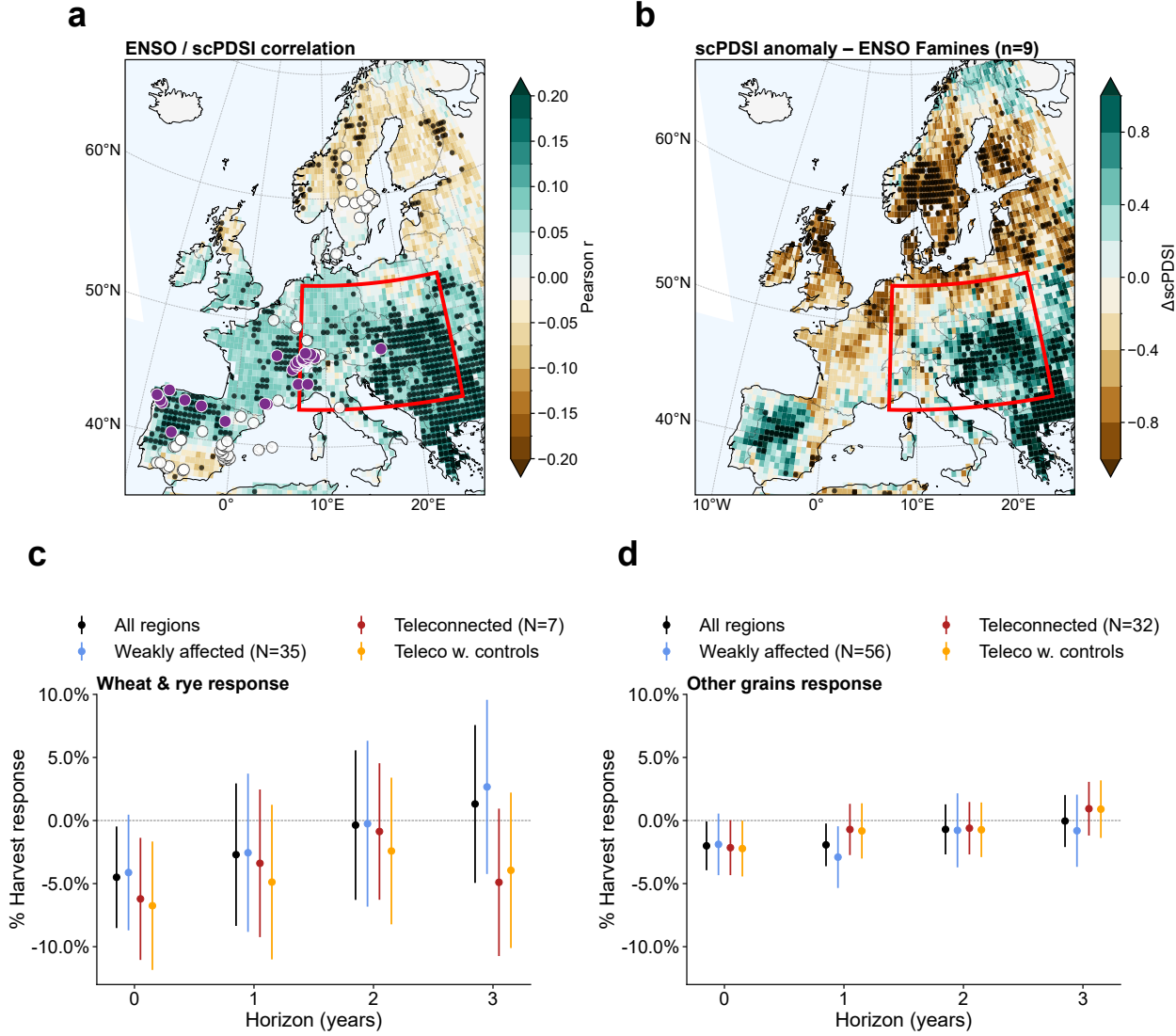


Figure 3: **ENSO teleconnections and grain harvest responses.** Correlation map of ENSO (NINO3.4 index) and (A) June–August scPDSI ([42]) over the entire period (1500–1800). Dotted grid-points show significant Pearson correlations at the 10% level. (B) Composite scPDSI anomalies, defined as ENSO famine years (as identified by the ML classifier) minus all other years. Dotted grid-points show significant difference in means at the 10% level using a t -test. Red outline highlights Central Europe. Purple dots indicate grain harvest locations in regions strongly affected by teleconnections, while white dots represent areas with weaker or negligible teleconnection influence. (C) Impulse response functions to a $+1^\circ\text{C}$ ENSO shock on rye and wheat grain harvests, and (D) on other grain harvests (see legend for colors). Whiskers correspond to the 95% confidence interval with Driscoll-Kraay standard errors. The groups include ‘Teleconnected’ IRFs referring to records whose scPDSI is correlated with ENSO at 10% significance and ‘Weakly affected’ IRFs, estimated on the records that exhibit no significant scPDSI correlation. ‘Teleco w. controls’ IRFs are estimated on teleconnected locations and include (as controls) annual NAO and Jet Stream indices, and measures of armed conflict

case if ENSO conditions had been neutral.

In testing the robustness of this finding, we note that estimates remain similar across additional models that control for the influence of climate-related and conflict-related observables as well as model specifications that account for unobserved heterogeneity in the assembled panel data (Figure 4A). Our results are also robust to other alternative model specifications and falsification exercises (Supplementary S9.1 and S9.3). We additionally confirm that the proportional hazards assumption holds for all models in Figure 4A. Global tests of proportional hazards [51] thus yield p -values consistently above 0.1 (Supplementary S6), supporting our use of the proportional hazards framework.

We also note that while hazard ratios capture relative differences in instantaneous risk, survival curves convey the cumulative effect on famine duration for different counterfactual scenarios. For example, as shown in Figure 4B, a $+2^{\circ}\text{C}$ ENSO anomaly (a severe El Niño) increases the modeled probability that a famine would persist beyond three years by roughly 28 percentage points compared with a -1°C ENSO anomaly (a La Niña event). We note that scaling to 2°C targets very extreme ENSO conditions, which were observed only twice in the 301 years (1500–1800) under study.

Finally, we find that ENSO emerges as a key out-of-sample predictor of famine persistence, reinforcing the claim that it was strongly linked to prolonged famines, as evidenced by linear and non-linear machine learning approaches to survival analysis, through a robust cross-validation procedure (see Figure 4C; more details in Methods 4.4). Across all models, ENSO stands out as the only consistently essential predictor, as reflected by its high permutation importance (4D), quantifying the loss in predictive skill when ENSO is removed from the model. Similar patterns of importance are observed when evaluating in-sample performance over the full period (Supplementary S7).

Market integration and price shock propagation Whereas the role of ENSO in triggering famine onset in teleconnected regions is explicable via a direct pathway from climate impact to diminished harvests (as observed), the role of ENSO in prolonging famine duration across Europe (including regions without notable teleconnections) requires further explanation. We first exclude the possibility that ENSO-related famines coincide with adverse hydroclimatic or temperature conditions outside the teleconnected regions. As shown in Extended Data Figure 3, across a wide range of definitions of ENSO-related famines in Central Europe, including both our model-based classification and simpler alternatives, scPDSI values are statistically significantly higher in teleconnected regions, particularly Central Europe. This pattern is consistent with our above-proposed mechanism and provides little evidence of concurrent adverse conditions elsewhere.

By contrast, one plausible explanatory mechanism involves the transmission of price shocks from teleconnected regions to other markets, including those already experiencing famines, contributing to their extension. This is consistent with the fact that Central Europe, with constituent territories such as Poland famously

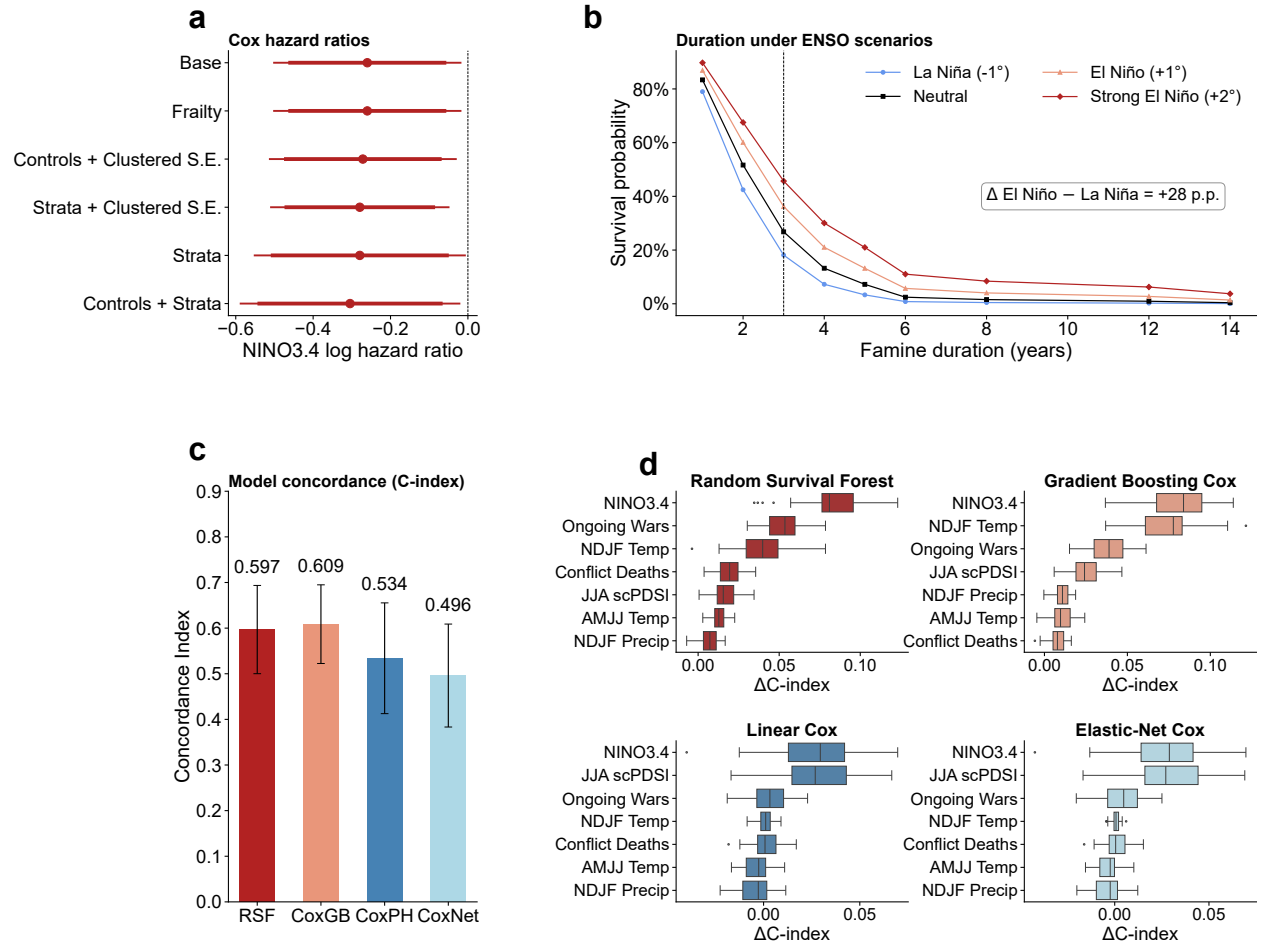


Figure 4: ENSO anomalies and famine duration. (A) Estimated log-hazard ratios for the ENSO index across various model specifications and controls. “Clustered S.E.” denotes models with standard errors clustered at the famine level. “Controls” include the NAO and Jet Stream Latitude reconstructions and conflict exposure. “Strata” indicates Cox models stratified by region. “Frailty” incorporates a random effect to account for unobserved heterogeneity or dependencies within a population. Error bars represent 90–95% confidence intervals. (B) Modeled survival curves for famine duration under varying ENSO anomaly scenarios using the “base” Cox Proportional Hazards model without region-level stratification. $\Delta = 28$ p.p. indicates that the probability of a famine persisting after 3 years is higher by 28 percentage points in the 3°C increase from La Niña to El Niño. (C) Cross-validation performance measured by concordance indices of four survival models: Standard Cox Proportional Hazards (CoxPH), Cox regression with elastic net regularization (CoxNet), Random Survival Forest (RSF), and Gradient Boosted Cox Regression (CoxGB). All models are fine-tuned using a grid search with 10-fold cross-validation, nested within an outer 10-fold cross-validation loop to evaluate out-of-sample performance. Error bars reflect the variation in concordance indices across folds. (D) Permutation Importance scores for each fine-tuned model, based on the decrease in Concordance Index (Δ C-Index) for $N = 50$ permutations.

known as the ‘granary of Europe’[52], was among the few regions of the continent that regularly produced grain surpluses for export [53]. Thus, shortfalls here could impact food access and propagate price increases more widely[11]. To test this hypothesis, we exploit grain price data alongside fish prices as comparator.

ENSO impact on grain and fish prices The available grain price series are identified according to 46 major European cities, while the fish price series cover seven cities (see Methods 4.1 for details on sources). We find that ENSO triggered a broad-based rise in prices across cities, even in weakly teleconnected locations (which comprise the majority of our grain series for the period). We estimate that a +1 °C ENSO shock led to a cumulative increase in grain prices of up to 6.5% (CI [3.8%, 9.4%]) after one year, with prices gradually returning to baseline over an eight-year horizon (Figure 5A). As per our harvest results, these impulse responses are designed to isolate the impact of an ENSO shock on inter-annual price fluctuations, controlling for other sources of variability.

This suggests a pan-European market response to regional harvest failures that is understandable in the context of the extensive market integration and associated grain trade in early modern Europe [11, 54, 55, 56]. A large literature documents that early modern European markets exhibited significant though spatio-temporally uneven integration. Studies of grain market show that integration was already notably present in the 16th century, then stagnated or even weakened during the 17th century, partly due to conflicts such as the Thirty Years’ War (1618–1648), but recovered in the 18th century, though again with substantial regional heterogeneity [11, 55, 57, 58].

In contrast to the immediate effects observed in grain prices, we find that marine fish prices started rising approximately two years following a +1 °C ENSO shock, peaking (approximately) at a 4.3% (CI [0.8%, 7.9%]) increase after three years (Figure 5B). However, we see no strong evidence of a corresponding post-ENSO-shock response in historical fish catches from North Atlantic or European waters (herring and cod; see Supplementary S8). We thus posit that the observed price response largely reflects a demand substitution effect arising from ENSO-related grain scarcity, rather than an impact on the marine environment affecting marine productivity and limiting the supply of catchable herring and cod. This is consistent with documentation of a minimal ENSO impact on present North Atlantic fisheries (see Bertrand et al. [59]).

The delayed (post-ENSO shock) increase in historical fish prices suggests that dietary substitution to fish occurred gradually following poor grain harvests. Households may at first have preferentially relied upon alternative strategies such as stored grains, substitute crops, or increased reliance on imported grains before meaningfully shifting consumption to fish[6, 7]. Cod markets, much like grain markets, exhibited signs of growing integration and functioned as partial substitutes for staple cereals [60]. Grain storage, to a certain extent, leveled out demand-driven price peaks after individual years of poor harvests, but was insufficient to meet demand for longer periods or after consecutive poor harvests in the early modern period [61, 62].

Demand substitution can, thus, be expected to increase the second year after harvest failure.

We also observe differential responses between fish types: cod prices increased by roughly 6.1% (CI [2.1%, 10.2%]) for a +1 °C ENSO shock, whereas herring prices increased by 2.1% (CI [−2.2%, 7.7%]). Both responses peaked three years post-shock, although cod prices began to respond (one year) earlier. These different responses suggest that market accessibility and value influenced substitution patterns. Cod, being more affordable and widely available, may have served as a more immediate grain substitute. The notion of cod as so-called ‘food for the poor’ (or, in reality, a staple for the working population) has been discussed by Hitzbleck [63] for Germany and by Grafe [64] for Spain, and is consistent with our results. In contrast, herring, particularly influenced by the higher-value Dutch herring trade, was relatively more expensive, potentially explaining its more delayed and muted price response to ENSO shocks (for more, see Allaire and Holm [65]).

As before, we verify that our results for grain and fish price responses are robust to alternative model specifications, and find this to be so (Supplementary S9.1). Placebo regressions with fully randomized ENSO histories thus generate no systematic price responses, with estimates centered near zero. In contrast, the observed effects (using the true, observed ENSO history) do not intersect with these null distributions (Supplementary S9.3). Using alternative grain price compilations to that of Ljungqvist and Seim [11] yields similar estimates (Supplementary S9.2), and we further show that spatial and temporal autocorrelation do not drive our statistical inferences (Supplementary S9.6).

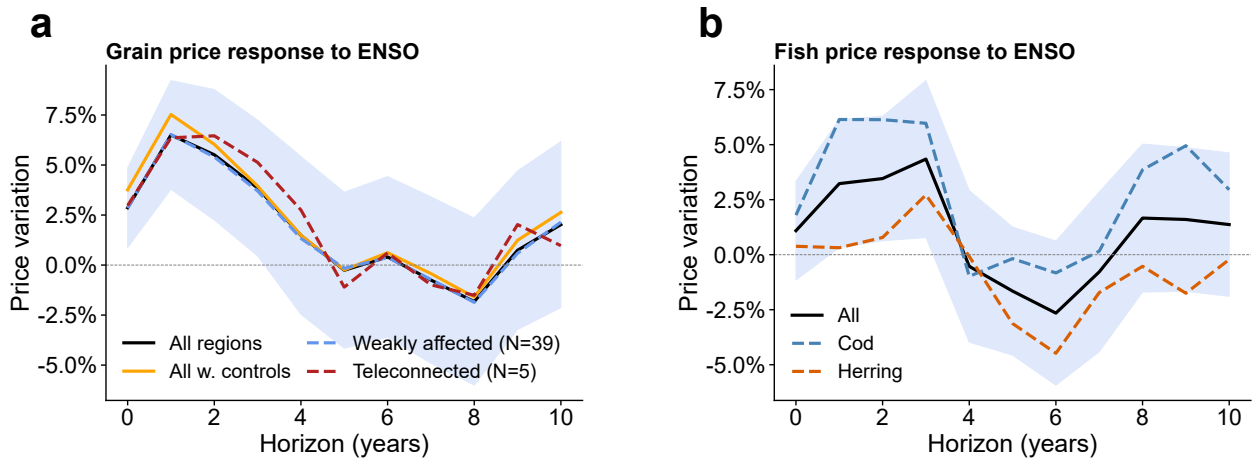


Figure 5: ENSO shocks broadly raised staple food prices. (A) Impulse response functions (IRFs) to a +1 °C ENSO shock on grain prices. The groups include ‘Teleconnected’ IRFs referring to cities whose scPDSI is correlated with ENSO at 10% significance and ‘Weakly affected’ IRFs, referring to the records that exhibit no significant scPDSI correlation. ‘All w. controls’ IRFs include NAO and Jet Stream Latitude reconstructions, the number of ongoing wars and the estimated conflict fatalities per year. (B) Impulse response functions of a +1 °C ENSO shock on fish prices, differentiated by species (Cod and Herring). Shaded areas correspond to the 95% confidence interval of the baseline models (black lines).

3 Discussion

We provide the first robust evidence that ENSO – more typically associated with tropical and subtropical impacts – was statistically significantly associated with the onset of regionally specific Central European famines. To explain this we offer quantitative evidence of an active causal pathway by which ENSO repeatedly induced in early modern Europe (1) excessive summer wetness in Central Europe, (2) reduced harvest yields and (3) elevated grain prices. Moreover, we show that positive ENSO anomalies increased year-to-year famine persistence across all European regions studied, even if not acting as a direct trigger in regions with limited or no obvious ENSO climate teleconnections. We posit that this reflects (at least in part) the substantial grain market integration known for the period. Given this, Central European grain deficits may not only have restricted supplies ordinarily traded to other European regions, but created reverse demand on the local grain supplies of these regions, as well as potentially motivating deleterious behaviors including grain hoarding and price speculation. To assess the general plausibility of these indirect market-mediated pathways, we employ available European grain price data and show that prices rose following positive ENSO anomalies even in regions for which no convincing teleconnections were observed, nor clear harvest deficits. We note, however, that quality data on inter-regional grain trade volumes are not available for this period, so our interpretation of market-mediated transmission relies on price co-movements rather than observed trade flows.

To assess the robustness of our results, we first address the possibility of collinearity among large-scale climate drivers linked to ENSO. As shown in Extended Data Figure 1, our results for famine onsets and prices are not driven by other atmospheric modes: the estimated ENSO effects remain stable when we partial out variation associated with the Jet Stream Latitude and the North Atlantic Oscillation (NAO). Conversely, the effects of the NAO and Jet Stream are statistically insignificant or smaller in magnitude compared to those obtained for ENSO in our main specification. Taken together, these findings indicate that we are capturing an independent ENSO signal, rather than a composite effect of correlated large-scale climate drivers. Similarly, we find that ENSO effects appear independent of volcanic forcing (see Extended Data Figure 4).

Grain prices have long been central to the analysis of food shortages and famines [66, 67], often serving as key indicators for their timing and intensity [68]. We note that recent scholarship cautions against directly inferring famine conditions from high prices, even if grain prices generally reflect the broader food supply. [7, 69]. For example, state-level interventions such as emergency relief measures might prevent famine conditions while prices remain high. While acknowledging this, we nonetheless argue that the notable and consistent increases in grain prices following positive ENSO shocks provide compelling evidence that ENSO played an indirect role in extending famine durations broadly across Europe, beyond the core strongly teleconnected region of Central Europe, in the context of integrated grain markets.

Our findings contribute to longstanding debates over the relative roles of climatic, political and socioeconomic factors in explaining early modern famines[7, 70]. While some scholarship has emphasized direct climate impacts on food crisis in past societies, other studies privilege the role of markets, institutions, and entitlements in determining famine onsets and outcomes[71, 6, 72, 2, 7]. Our analyses provides quantitative evidence for historically situated environmental causation and market-mediated amplification mechanisms [73, 53]. The pronounced effects on famine persistence highlight the importance of sociopolitical and socioeconomic factors in prolonging subsistence crises beyond initial climate triggers [70, 5, 7]. These results support the view that early modern European famines emerged through complex interactions between climate variability, harvest failures and integrated grain markets, challenging both simple climate determinism and purely societal explanations [10].

We also note limitations in the principal data underlying our analyses. The ENSO reconstruction for the 1500–1800 period is based on 242 chronologies—fewer than half the number available after 1800. Nonetheless, Cook and Cane [33] show that reconstruction skill remains comparable, and emphasize that the index captures the remote effects of tropical Pacific SSTs on rainfall. We also note that the chronologies used by Cook and Cane [33] do not include European trees. Because they only include tree-ring records that strongly reflect these teleconnections, the resulting indices may serve as reliable indicators of ENSO impacts. Our study assesses teleconnections between ENSO and the European climate using multiple climate reconstructions, each with their own uncertainties. For example, the tree-ring-based June–August scPDSI reconstruction (known as the Old World Drought Atlas) that we use to infer soil moisture conditions is less skilled for some regions, in particular Eastern Europe[74]. To address this, we compared several reconstructions and saw recurring patterns, such as consistent soil moisture and precipitation teleconnections in Central and Eastern Europe. We acknowledge that limitations in these reconstructions may affect the identification of teleconnections. However, as shown in Extended Data Figure 2, our Central versus Rest of Europe partition yields statistically indistinguishable harvest responses to ENSO. This consistency strengthens our confidence in the robustness of the observed teleconnection patterns and the underlying mechanism we propose.

Finally, the famine year compilation by Ljungqvist et al. [7] offers a comprehensive list of major European famines for the entire early modern period. However, assembling a representative chronology of famines across different European regions is challenging. Many events were localized or sub-regional in nature[6], and their full geographic extent is often uncertain due to limitations of the available historical data[5]. Furthermore, distinguishing between outright famines and more moderate food shortages – based on contemporary definitions – is similarly complicated by the inconsistent nature of preserved historical sources[75].

We advance knowledge of how large-scale climate variability propagates through interconnected socioeconomic systems. This mechanism of climate impact transmission may help explain historical patterns of widespread societal disruption following major agriculturally adverse climate shocks, providing insights relevant to understanding climate vulnerability in interconnected modern food systems. In today’s global

food system, ENSO continues to modulate crop yields across up to two-thirds of global cropland [20] and El Niño events produce substantial economic losses [17]. These losses fall most acutely on food-insecure populations in sub-Saharan Africa, and parts of South Asia, Southeast Asia and Latin America, precisely the regions where ENSO teleconnections are strongest [24]. Modern studies confirm that ENSO continues to influence yields [18] and generate significant grain price volatility in contemporary markets [76, 77], suggesting that the transmission mechanism – from climate shock to food price – remains operative today despite vastly different institutional and economic conditions. This supports the “adaptation gap” argument of Carleton and Hsiang [78]: while modern economies may have partially adapted to ENSO, persisting significant effects suggest that these adaptations remain incomplete.

Future work should address the question of adaptation to famines across centuries. Economists have begun to account for human adaptation in their estimates of climate impacts[79][80] and further insights may arise in assessing how adaptation affects our estimates of ENSO’s impact on food security, especially in relation to the progress (plus advantages and disadvantages) of European food market integration. Our results should encourage a broader investigation into teleconnections between ENSO and the early modern European climate, a period coinciding with the main phase of the Little Ice Age[3]. Future studies can offer insights into how ENSO teleconnections have evolved over time, and how their triggering of climatic extremes may have impacted societies (not only in food security) both economically and socially.

4 Methods

4.1 Data

4.1.1 Famine chronology

We use the most recent compilation of famines in early modern Europe from Ljungqvist et al. [7], who revised and updated the lists from Alfani and Ó Gráda [5] [81] to provide a comprehensive chronology of famine years. The following European regions from 1250 to 1800 were included: Central Europe, France, Great Britain, Ireland, Italy, the Low Countries, the Nordic countries, Spain, and Ukraine/Russia (and Belarus). The list of famine years only indicates the presence of famine conditions within a region, but does not inform us about neither the severity nor the geographical extent of the famine within the given region. For most pre-19th-century European famines, such information is unavailable because of source limitations.

4.1.2 Climate reconstructions

We used a recently published tree-ring-based ENSO reconstruction from Cook and Cane [33]. This climate field reconstruction of tropical Pacific sea surface temperatures (HadISST [82]) for boreal winter (December–February) is based on a circum-Pacific tree-ring network from regions known to be affected by El Niño rainfall. The dominant mode of the SST field was skillfully reconstructed back to 1100 CE and captures long-term variability of El Niño exceptionally well back to 1500 CE [33]. Our metric for ENSO is the NINO3.4 region (5°N–5°S, 170°W–120°W). We used the anomaly in degree Celsius sea surface temperature (SST) for each region, measured as the deviation from the 1801–1900 mean SST. This targets only the boreal winter season (December–February), when ENSO has the strongest effect on global climate.

Our climate analysis focuses on late spring and early summer temperature and precipitation (average of April–July, AMJJ), winter temperature and precipitation (average of November–February, NDJF) and June–August (JJA) soil moisture. The seasonal window April–July captures the main growing season for grains of all types across Europe during the early modern period. While autumn-sown wheat and rye, as shown by [47], were influenced by winter conditions in parts of Europe, the key season was still late spring and early to mid summer.

For temperature and precipitation, we use the ensemble mean 2-meter air temperature and total precipitation from the Modern Era Reanalysis (ModE-RA) [41]. ModE-RA is a global monthly paleo-reanalysis covering the period 1421 to 2008. To reconstruct past climate fields, an offline data assimilation approach is used, blending information from an ensemble of transient atmospheric model simulations and instrumental observations. In the early period, ModE-RA utilizes natural proxy data and documentary data, while from

the 17th century onward, instrumental measurements are also assimilated[83]. Mode-RA is systematically assessed through comparisons with independent time series, gridded instrumental observations, and other proxy-based paleoclimate reconstructions. Unlike most paleo-reanalyses, which rely on non-transient priors from climate simulations with low-frequency variability driven by the assimilated proxy data, Mode-RA derives its centennial-scale variability from the model’s response to external forcings. We take advantage of Mode-RA’s monthly temporal resolution – compared to earlier reconstructions by Luterbacher et al. [84] and Pauling et al. [85] – to flexibly construct temperature and precipitation maps for April–July (AMJJ) and November–February (NDJF).

For soil moisture, we use the Old World Drought Atlas (OWDA) [42]. The OWDA is a gridded, annually resolved reconstruction of summer (June–August, JJA) hydroclimatic variability across Europe and North Africa over the past millennium. It is based on an extensive network of tree-ring chronologies from living, archaeological, and sub-fossil material, standardized to preserve long-term variability. The applied climate field reconstruction method was the point-by-point regression with ensemble weighting against the self-calibrating Palmer Drought Severity Index (scPDSI). The OWDA provides year-to-year maps of drought and pluvial conditions on a 5,414-point $0.5^\circ \times 0.5^\circ$ longitude–latitude grid, which enables detailed characterization of hydroclimatic variability during the early modern period in Europe.

We further incorporate state-of-the-art reconstructions of additional large-scale climate drivers to isolate the effect of ENSO. Specifically, we use the calibrated North Atlantic Oscillation (NAO) reconstruction from Ortega et al. [38] and the Jet Stream Latitude (JSL) reconstruction from Xu et al. [39]. Both variables are available at the annual scale and capture broad, hemispheric-scale circulation patterns.

For our panel of famine periods, we assign every region a unique scPDSI/temperature/precipitation value every year based on the spatial average over that region. For subsequent analyses conducted at the sub-regional level (i.e. city, district or estate), we geocode each location and assign the grid-cell(s) closest to its latitude and longitude coordinates to extract local climate values. The temperature and precipitation data are provided at a spatial resolution of $1.8^\circ \times 1.8^\circ$, while the scPDSI data are at a finer resolution of $0.5^\circ \times 0.5^\circ$. We use a $1^\circ \times 1^\circ$ radius around the coordinates for the scPDSI in order to match the coarser temperature resolution. This larger radius also smooths our ENSO–scPDSI teleconnection partitions. Note that, in order to weight the scPDSI, temperature and precipitation fields according to their area on a sphere, each grid point is multiplied by $\sqrt{\cos \phi}$ where ϕ is the latitude.

4.1.3 Commodity prices and grain harvests

We use annual grain price time-series published by Ljungqvist and Seim [11], for a given city and year. We show our results are similar when using other grain price compilations in Supplementary S9.2. For

fish prices, we use a compilation that spans seven European cities (Antwerp, Barcelona, Bergen, Gdansk (Danzig), London, Munich and Vienna), with cod and herring prices, deriving from Matthews [60], Allaire and Holm [65] and the Allen-Unger Global Commodity Prices Database[86].

We included an extensive compilation of quantitative harvest data from the published literature (much of which was also included in Ljungqvist et al. [47]). The dataset includes harvest data from present-day Denmark, France, Germany, Hungary, Spain, Switzerland, and Sweden. We utilized three main types of harvest data: (1) tithe records from regions where tithes reflected actual fluctuations in harvest size, (2) yield ratios – measuring the quantity harvested relative to the amount sown – from individual farms and estates, and, more rarely, (3) total yield quantities recorded for individual farms, estates, or larger districts.

A detailed list of references for the grain harvest and price data is provided in Supplementary S1.

4.1.4 Armed conflict measures

To estimate the annual number of conflict fatalities in Europe as a whole, we use the Conflict Catalog, a taxonomy of the most severe recorded armed conflicts [37]. To calculate the yearly fatalities from events spanning multiple years, the total fatalities for each event are evenly distributed across all the years of its duration. This method aggregates overlapping events by summing their contributions within each year. Although the assumption of even distribution across years may be less accurate for protracted conflicts such as the Thirty Years’ War (1618–1648), no reliable source provides annualized fatality estimates for such multi-year events, to our knowledge.

Similarly we compute the number of ongoing wars in a given year, and the number of wars started in a given year, which we use as our main measure of conflict onset.

4.2 ENSO and the Onset of Famine Periods

Causal Inference We examine the causal impact of ENSO on the onset of famine periods using a fixed-effects linear probability model. Specifically, we estimate the conditional probability of famine onset as:

$$\mathbb{P}(\text{Onset}_{i,t} = 1) = \alpha_i + \gamma_{\text{Decade}(t)} + \delta_i \cdot \text{ENSO}_t + \mathbf{x}_{i,t}\beta + \varepsilon_{i,t} \quad (1)$$

where $\text{Onset}_{i,t}$ is an indicator equal to 1 if region i experiences a famine in year t but not in year $t - 1$, and 0 otherwise. Here, α_i denotes region fixed effects, which absorb time-invariant regional characteristics; $\gamma_{\text{Decade}(t)}$ captures decade fixed effects; $\delta_i \cdot \text{ENSO}_t$ allows for region-specific sensitivity to ENSO anomalies

(measured using the NINO3.4 index); and $\mathbf{x}_{i,t}$ is a vector of time-varying control variables. The error term is denoted by $\varepsilon_{i,t}$.

We first estimate this relationship using a linear probability model, which provides a transparent baseline for interpreting marginal effects. In the following section, we relax the linearity assumption using a more flexible, nonlinear specification. Standard errors are corrected for autocorrelation and heteroskedasticity using Driscoll–Kraay standard errors.

The fixed effects in Equation 1 are central to our identification strategy. By absorbing location-specific and time-trending influences on famine onset non-parametrically, they isolate the contribution of ENSO from both observed and unobserved confounders. This approach is more robust than attempting to enumerate and control for the other possible drivers of famine directly. In effect, the specification attributes variation in famine onset to idiosyncratic ENSO shocks within a region and year, supporting a causal interpretation of the parameter δ_i . We also report results of these regressions in table form, as well as a similar logistic regression model in Extended Data Table 1.

Machine Learning Attribution We next quantify the contribution of ENSO and other predictors (regional temperature, precipitation, soil moisture, and armed conflict) to famine onsets in Central Europe using a Gradient Boosting classifier [87]. This approach relaxes the linearity assumption and captures potentially complex, nonlinear interactions among covariates.

Formally, the fitted model defines a nonlinear mapping f :

$$\mathbb{P}(\text{Onset}_t = 1 \mid \mathbf{x}_t, \text{ENSO}_t) = f(\mathbf{x}_t, \text{ENSO}_t)$$

where $\mathbf{x}_t$ is the vector of covariates at time t and ENSO_t is the NINO3.4 index anomaly.

Model hyperparameters were tuned via 10-fold cross-validation to maximize predictive accuracy for classifying each year as a famine onset or non-onset (see Table 1 for the grid).

Using the fine-tuned model, we estimate the number of Central European famine onsets attributable to positive ENSO anomalies. Let $\mathcal{T}_+ = \{t : \text{Onset}_t = 1, \text{ENSO}_t > 0\}$ denote the observed famine-onset years with a positive NINO3.4 anomaly, and define the counterfactual ENSO series

$$\text{ENSO}_t^{\text{CF}} = \begin{cases} 0, & t \in \mathcal{T}_+, \\ \text{ENSO}_t, & \text{otherwise.} \end{cases}$$

The model is evaluated under both the observed and counterfactual ENSO series,

$$\hat{\text{Onset}}_t^{\text{OBS}} = \mathbf{1}\{f(\mathbf{x}_t, \text{ENSO}_t) \geq \tau\}, \quad \hat{\text{Onset}}_t^{\text{CF}} = \mathbf{1}\{f(\mathbf{x}_t, \text{ENSO}_t^{\text{CF}}) \geq \tau\},$$

481 using a fixed classification threshold of $\tau = 0.5$. The number of famine onsets attributable to positive ENSO
482 anomalies is then

$$N_{\text{ENSO}} = \sum_t \text{Onset}_t \left(\hat{\text{Onset}}_t^{\text{OBS}} - \hat{\text{Onset}}_t^{\text{CF}} \right),$$

483 which counts historical famine onsets correctly identified under the observed ENSO conditions but not under
484 the counterfactual.

485 Model performance was evaluated both in-sample and out-of-sample via cross-validation, providing a ro-
486 bust assessment of the classifier’s predictive skill. We show that using different subsets of predictors yields
487 comparable results in Supplementary [S3](#).

Table 1: Hyperparameter grid used for tuning the Gradient Boosting Classifier via cross-validation.

Model	Hyperparameters
Gradient Boosting Classifier	Maximum depth $\in \{1, 3, 5, 10\}$
	Number of estimators $\in \{3, 5, 10, 50\}$
	Learning rate $\in \{0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5\}$
	Subsample $\in \{0.7, 0.9\}$
	Maximum features $\in \{\sqrt{\cdot}, 0.5\}$
	Minimum samples per leaf $\in \{2, 5\}$
	Minimum samples per split $\in \{5, 10\}$

4.3 Dynamic Causal Effect of ENSO on Prices and Harvests

We estimate the dynamic causal effects of global temperature shocks using panel local projections [49]. Specifically, for each horizon $h = 0, \dots, H$, we estimate the following regressions:

For grain harvests, where g indexes grain type, r indexes the harvest proxy (tithe, yield, or yield ratio), $\delta_{i,g,r,h}$ are record fixed effects, $\phi_i t$ is a record-specific linear time trend, and $T_i \in \{0, 1\}$ indicates whether record i is teleconnected to ENSO, we estimate:

$$\begin{aligned} \ln(\text{GrainHarvest}_{i,g,r,t+h}) - \ln(\text{GrainHarvest}_{i,g,r,t-1}) = & \theta_h \text{ENSO}_t + \psi_h (T_i \cdot \text{ENSO}_t) + \mathbf{x}'_{i,t} \boldsymbol{\beta}_h \\ & + \delta_{i,g,r,h} + \gamma_{h,\text{Decade}(t)} + \phi_i t + \varepsilon_{i,g,r,t+h}, \end{aligned} \quad (2)$$

θ_h is the baseline response on weakly-affected records and $\theta_h + \psi_h$ is the response on teleconnected records. The control vector $\mathbf{x}_{i,t}$ includes three lags of ENSO ($\text{ENSO}_{t-1}, \text{ENSO}_{t-2}, \text{ENSO}_{t-3}$) in all three specifications.

For grain prices:

$$\begin{aligned} \ln(\text{GrainPrice}_{i,t+h}) - \ln(\text{GrainPrice}_{i,t-1}) = & \theta_h \text{ENSO}_t + \psi_h (T_i \cdot \text{ENSO}_t) + \mathbf{x}'_{i,t} \boldsymbol{\beta}_h \\ & + \delta_{i,h} + \gamma_{h,\text{Decade}(t)} + \varepsilon_{i,t+h}, \end{aligned} \quad (3)$$

where $\text{GrainPrice}_{i,t}$ is the price of grain in city i at time t , $\delta_{i,h}$ represents city fixed effects.

For fish prices, where s indexes species (Cod / Herring), $\delta_{i,s,h}$ are city-species fixed effects, and D_s is a species indicator, we estimate:

$$\begin{aligned} \ln(\text{FishPrice}_{i,s,t+h}) - \ln(\text{FishPrice}_{i,s,t-1}) = & \theta_h \text{ENSO}_t + \psi_h (D_s \cdot \text{ENSO}_t) + \mathbf{x}'_{i,t} \boldsymbol{\beta}_h \\ & + \delta_{i,s,h} + \gamma_{h,\text{Decade}(t)} + \varepsilon_{i,s,t+h}, \end{aligned} \quad (4)$$

θ_h and $\theta_h + \psi_h$ capture the dynamic causal effect of interest at horizon h , which we interpret as the impulse response function. $\mathbf{x}_{i,t}$ is a vector of potential control variables (including 3 lags of ENSO in the main models), and $\gamma_{\text{Decade}(t)}$ are decade fixed effects that control for common long-run trends across locations. The error term $\varepsilon_{i,t+h}$ may be serially correlated. The inclusion of fixed effects is essential for the causal interpretation of these parameters, as they absorb location-specific factors and decadal trends, isolating the effect of ENSO shocks from confounding factors, just as the fixed-effects specification in Equation 1. Our main findings remain robust across an alternative model specification, as discussed in Supplementary S9.1. Because the ENSO shock does not vary by location, the error term may exhibit both serial and cross-sectional dependence. For inference, we therefore rely on Driscoll and Kraay [88] standard errors, which are robust to such dependence. In the Supplementary Information S9, we further assess robustness using alternative estimators that explicitly account for spatial autocorrelation. We set $H = 4$ for grain harvests and a longer horizon of $H = 10$ for prices, as price responses to climatic shocks are likely to exhibit greater persistence than harvests.

4.4 Survival Analyses of Famines

Inference To evaluate how ENSO influences the hazard of famine termination, we use a Cox Proportional Hazards model [89]. We estimate the effect of time-varying ENSO conditions on the hazard of event termination using a time-dependent Cox Proportional Hazards model with stratification by region, which allows the baseline hazard to vary across regions. The hazard function for famine i in region r at time t is specified as:

$$h_i(t \mid \text{ENSO}_i(t), \mathbf{X}(t), r) = h_{0r}(t) \exp \left(\beta \cdot \text{ENSO}_i(t) + \gamma^\top \mathbf{X}(t) \right), \quad (5)$$

where: $h_i(t \mid \cdot)$ is the hazard rate for famine i at time t ; $h_{0r}(t)$ is an unspecified *region-specific* baseline hazard for region r ; $\text{ENSO}_i(t)$ is a time-varying covariate capturing ENSO conditions (NINO3.4 index) at time t for famine i ; β is the coefficient capturing the sensitivity of the hazard with respect to ENSO; $\mathbf{X}(t)$ is a vector of time-varying control covariates; and γ is the corresponding vector of coefficients.

In the Cox Proportional Hazards framework, coefficients are estimated on the log-hazard scale. The coefficient β corresponds to a hazard ratio (HR) of $\exp(\beta)$. This hazard ratio represents the multiplicative change in the hazard of famine termination associated with a $+1^\circ\text{C}$ increase in ENSO, holding other variables constant. The percentage change in hazard can then be computed as $(\exp(\beta) - 1)$.

By stratifying the baseline hazard across regions, the model flexibly accounts for unobserved regional heterogeneity in baseline famine risks while still estimating a common effect of ENSO and other covariates. We verify the robustness of our estimates by including additional time-varying controls, such as temperature and precipitation anomalies and the number of wars in a given year, and by comparing specifications with clustered standard errors and region-level frailty terms. Incorporating these controls and modeling choices is important for causal interpretation, as they help account for potential confounding factors and unobserved heterogeneity that could otherwise bias the estimated effect of ENSO on famine duration.

Machine Learning Prediction For our predictive exercise, we use four different survival models: a standard Cox Proportional Hazards regression, an Elastic-Net Cox Regression [90], a Random Survival Forest [91] and a Gradient Boosting Survival Analysis, i.e. a Gradient-boosted Cox proportional hazard loss with regression trees as base learner ([92]). All models use the average values of the selected predictors (NINO3.4, temperature and precipitation indices, JJA scPDSI, and armed conflict measures) over the famine period, with famine duration as the outcome variable.

We employ a cross-validation (CV) approach to estimate out-of-sample performance. The nested cross-validation procedure ensures that hyper-parameter tuning does not bias the estimate of out-of-sample per-

542 formance. By performing an inner CV to select the best hyper-parameters and an outer CV to evaluate model
543 performance, we obtain an unbiased estimate of the concordance index for unseen data.

544 The training and evaluation procedure for each model is as follows:

- 545 1. Define an outer $k = 10$ fold cross-validation split to evaluate model performance on unseen data.
 - 546 (a) Within each outer training fold, perform an inner $k = 10$ fold cross-validation to tune hyper-
547 parameters via a grid search. Select the hyperparameter combination that maximizes the mean
548 concordance index (C-index) across the inner folds. The specific hyperparameter grids used in
549 this search are detailed in Supplementary S7.
 - 550 (b) Refit the model with the selected hyperparameters on the entire outer training fold and evaluate
551 its predictive performance (concordance index) on the corresponding outer test fold.
- 552 2. Aggregate the performance estimates across all outer folds to obtain the model's out-of-sample con-
553 cordance index (mean and standard deviation).
- 554 3. After completing the nested cross-validation, refit each model on the full dataset using the best hy-
555 perparameters identified in the inner loops, and compute permutation feature importances to assess
556 variable contributions to predictive performance.

557 4.5 Robustness Checks

558 We conduct a series of robustness checks to test the sensitivity of our findings on famine onsets, duration,
559 grain and fish prices, and agricultural yields to modeling assumptions, data sources, and inference methods.
560 A summary is provided in Table S11.

561 **Permutation Tests** We assess the robustness of our results by randomly permuting the ENSO sequences
562 across years in the panel datasets and re-estimating the models. The observed effects consistently fall well
563 outside the 95% confidence intervals of the resulting placebo distributions (Figs. S16, S17).

564 **Alternative Data Sources** Using the grain price dataset from Federico et al. [55] and Allen [93] results in
565 impulse responses nearly identical to our main analyses using Ljungqvist and Seim [11] (Figs. S14a, S14b).
566 Using the earlier, less extensive, compilation of yield ratio time-series of Slicher van Bath [50], we again find a
567 strong ENSO effect, if anything larger than in our estimates (Fig. S15). This result likely reflects the narrower
568 coverage of the Slicher van Bath [50] dataset, which includes a high share of Central European time series.

Alternative Model Specifications We re-estimate the effects of ENSO on famine duration using parametric hazard models (Weibull, log-logistic, Tobit), which consistently indicate significant positive effects of ENSO anomalies on famine duration (Table S12). Additionally, we use fixed-effects regressions to model famine duration, grain prices, and harvests. These models, including contemporaneous and lagged ENSO shocks, confirm strong and persistent effects (Tables S13–S17). We also reject evidence of non-linear impacts of ENSO on famine onsets and prices (Figure S13).

Sample Composition We show that our main results are robust to alternative samples and exclusion tests. The dynamic effects of ENSO on prices and harvests are largely insensitive to excluding one location at a time or to dropping 20-year blocks, leaving the impulse responses unchanged (Figs. S19–S24). Similarly, our famine onset and duration results are robust to excluding individual famine episodes, with baseline estimates remaining well within the range of leave-one-out re-estimates (Fig. S18).

Inference and Standard Errors Our results are robust to alternative standard error corrections, including Conley spatial clustering and two-way clustering (Figure S25).

Reverse Causality Granger causality tests reject the possibility that grain prices or harvests predict ENSO anomalies, alleviating concerns of reverse causality (Table S18).

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The authors declare no competing interests.

Author Contributions

Conceptualization: E.E., M.J.P., F.L., P.H., E.J., F.C.L.

595 Data curation: F.L., F.C.L.

596 Formal analysis: E.E., J.K.

597 Writing – original draft: All authors

598 Writing – review & editing: All authors

599 **Data availability**

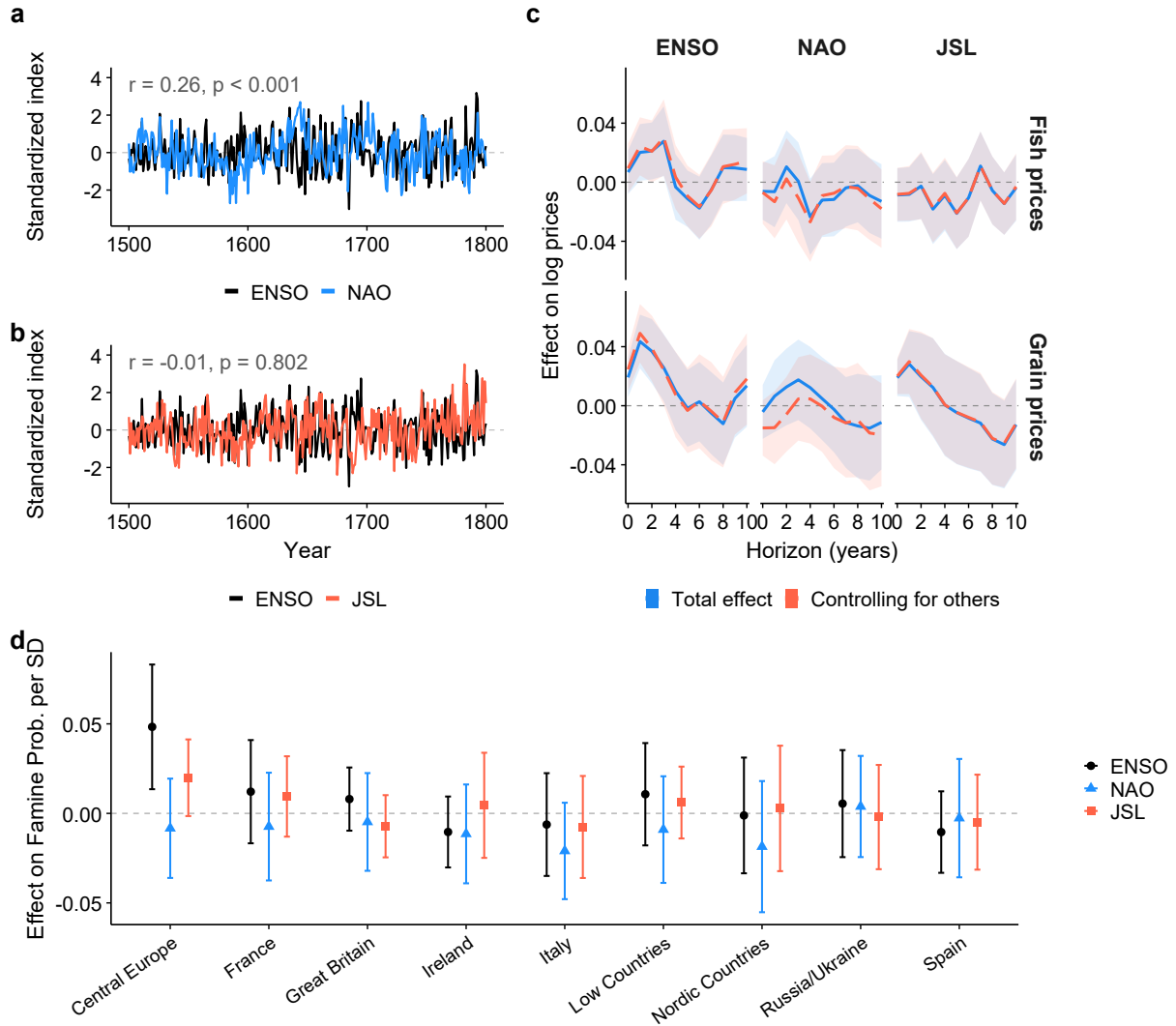
600 All the codes and datasets used for this study can be found at <https://github.com/emileDesmaili/enso-famine-paper>

Table 2: **Extended Data Table 1:** Effect of a 1°C Anomaly in the Nino 3.4 Index on the Probability of a Famine Start

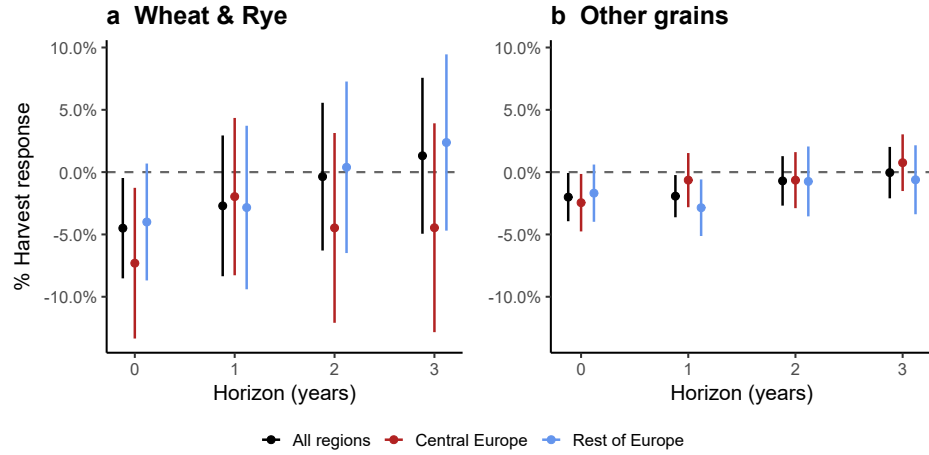
Dependent Variable:	Famine Start					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	Logit	OLS	Logit
<i>Variables</i>						
Nino3.4 × Central Europe	0.0723*** (0.0261)	0.0689*** (0.0262)	0.0732*** (0.0257)	1.110*** (0.3522)		
Nino3.4					0.0100 (0.0077)	0.1850 (0.1383)
Decade FE	No	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Model	LPM	LPM	LPM	Logit	LPM	Logit
Standard Errors	DK	DK	DK	-	DK	-
<i>Fit statistics</i>						
AIC	-137.65	-125.30	-120.80	1,230.6	-121.77	1,228.3
BIC	-78.610	158.11	186.23	1,537.6	138.02	1,488.0
Observations	2,709	2,709	2,709	2,709	2,709	2,709
Squared Correlation	0.00602	0.02910	0.03035	0.02981	0.02496	0.02407

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

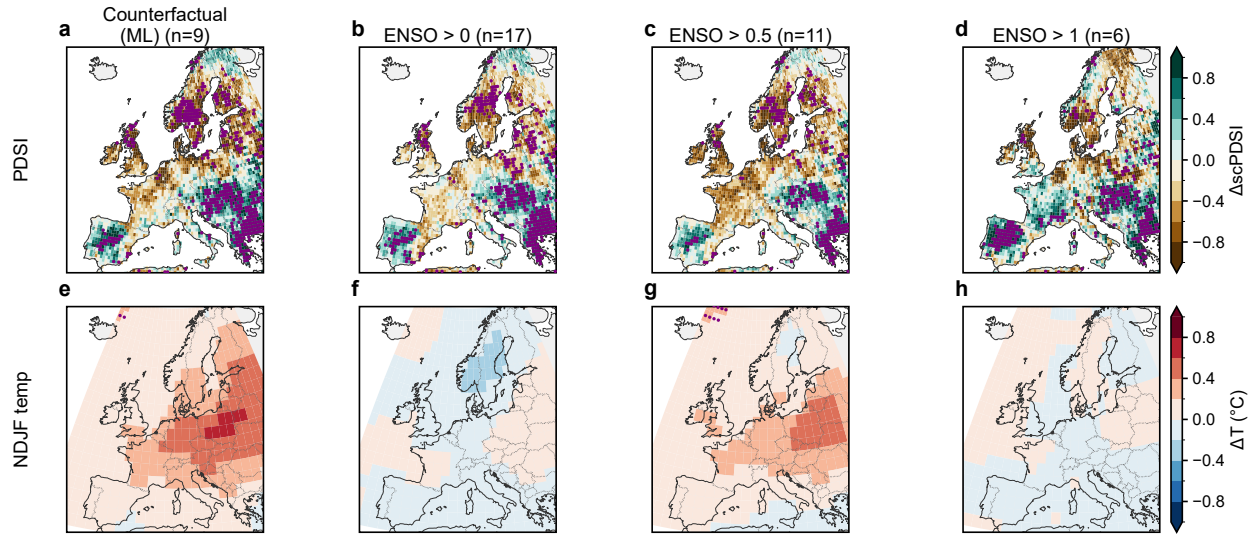
Logit columns report log-odds coefficients. DK = Driscoll–Kraay.



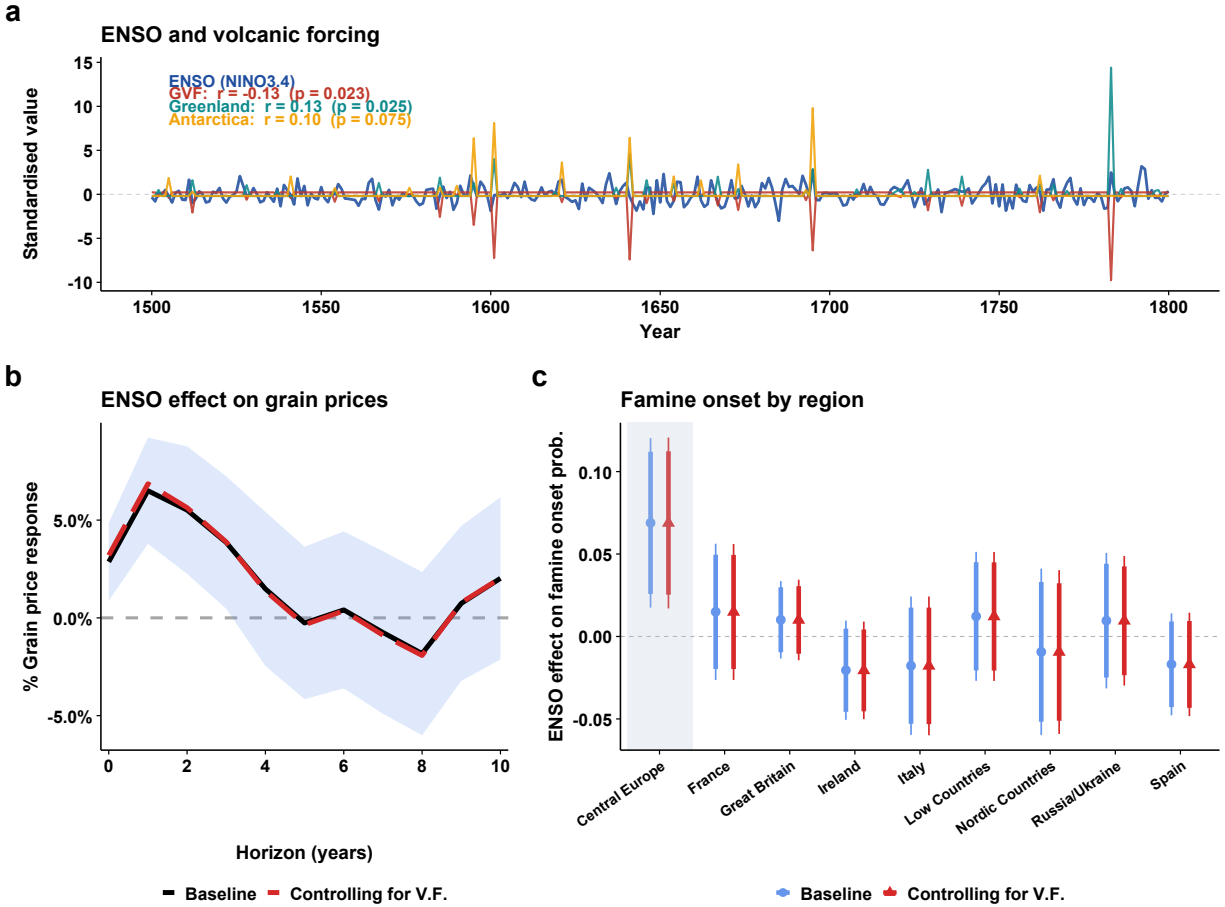
Extended Data Fig. 1: Relationship between ENSO, the North Atlantic Oscillation, and the Jet-Stream Latitude index, and their independent effects on prices and famine onset. **a-b)** Standardised time series of the annual NINO3.4 index (black), the North Atlantic Oscillation (NAO, vermillion), and the Jet-Stream Latitude index (JSL, blue) over the study period. Correlation coefficients and p -values for ENSO–NAO and ENSO–JSL are shown in each panel. **c)** Impulse response functions (IRFs) of log cod fish prices (top row) and log grain prices (bottom row) to a one-unit shock in ENSO, NAO, and JSL (columns), estimated via local projections with location and decade fixed effects and Driscoll–Kraay standard errors. Solid lines show the total effect of each index; dashed lines show the effect after controlling for the other two indices. Shaded bands denote 95% confidence intervals. **d)** Linear probability model coefficients for famine onset probability by European region, estimated in a panel regression with region and decade fixed effects. Points show point estimates; whiskers show 95% confidence intervals. All indices are in standardized units (standard deviations)



Extended Data Figure 2: Grain harvest responses to ENSO by geographic partition. Impulse response functions (IRFs) of log grain yields to a 1°C increase in the NINO3.4 index. **a.** Wheat and rye. **b.** Other grain types (barley, oats, mixed cereals). Series partition the sample geographically: All regions (pooled); Central Europe; Rest of Europe.



Extended Data Figure 3: European climate anomalies during ENSO-induced famine years in Central Europe, 1500–1800. Composite anomalies, defined as famine years minus all other years, of JJA drought and NDJF temperature across Europe are shown for four alternative definitions of ENSO-related famine years. The top row (**a–d**) displays self-calibrating Palmer Drought Severity Index (scPDSI) anomalies from the Old World Drought Atlas [42], and the bottom row (**e–h**) shows November–February (NDJF) surface temperature anomalies from the ModE-RA ensemble mean, relative to a 1901–2000 baseline. Columns correspond to four sets of famine years, all restricted to Central European famine onsets: (**a,e**) machine-learning counterfactual years, defined as onsets predicted by a gradient boosting classifier under observed ENSO conditions but not when ENSO forcing is set to zero; (**b,f**) years with a positive ENSO index; (**c,g**) moderate El Niño years; and (**d,h**) strong El Niño years. Purple dots denote grid points where the composite differences are statistically significant at the $p < 0.10$ level (t -test).



Extended Data Fig. 4: Volcanic forcing does not confound ENSO effects on food security. **a**, Standardized time series of the ENSO index (NINO3.4) and three volcanic forcing reconstructions – global volcanic forcing (GVF, W m^{-2}), Greenland ice-core sulfate (kg km^{-2}), and Antarctica ice-core sulfate (kg km^{-2}) – over the period 1500–1800 CE ([95]). Pearson correlation coefficients between ENSO and each forcing series confirm that volcanic eruptions and ENSO are weakly correlated in the sample. **b**, Local-projection impulse response of log grain prices to a 1°C positive NINO3.4 anomaly. The baseline specification (with location and decade fixed effects) is shown alongside a specification that additionally controls for contemporaneous GVF, Greenland sulfate, and Antarctica sulfate. Shaded bands denote 95% confidence intervals. Controlling for volcanic forcing leaves the ENSO price response essentially unchanged. **c**, Coefficients from a linear probability model of famine onset regressing NINO3.4 with region fixed effects and decade fixed effects, estimated with and without volcanic forcing controls. Whiskers show 90% (thick) and 95% (thin) confidence intervals based on Driscoll–Kraay standard errors. The ENSO effect on famine onset is robust to the inclusion of volcanic forcing across all regions.

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Supplementary Information

for “El Niño amplified food insecurity in early modern Europe”

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S1 Grain Prices and Harvest Data References

Here we present tables with references to all grain price and grain harvest data. The grain price data has been collected by Ljungqvist and Seim [1], while some of the grain harvest data have been published in Ljungqvist et al. [2].

Table S1: The dataset of 69 annual grain price series from Ljungqvist and Seim [1] with information about location (city), the covered period, missing values ('gaps') within the covered period (in percent), mean price (g Ag/l) for the covered period, coefficient of variation (CV) of the price for the covered period, the auto-correlation (AR1) value of the grain prices, and original data source(s). Only price series covering at least the common period 1590–1700, and with a maximum of 35% data gaps, are included.

City	Coverage	Gaps	Mean price	CV	AR1	Reference(s)
<i>Barley (11 series)</i>						
Augsburg	1500–1800	2%	0.35	0.66	0.70	Elsas [3]
Coimbra	1515–1800	14.74%	0.45	0.38	0.52	Palma and Reis [4]
England	1500–1800	0.33%	0.29	0.47	0.86	Rogers [5]
Gdansk	1501–1800	23%	0.27	0.42	0.82	Furtak [6]
Lisbon	1511–1800	18.69%	0.46	0.35	0.57	Palma and Reis [4]
New Castile	1504–1750	15.85%	0.33	0.56	0.74	Hamilton [7]
Paris	1520–1800	3.93%	0.32	0.50	0.52	Hoffman [8]
Speyer	1514–1799	32.84%	0.32	0.49	0.59	Elsas [3]
Strasbourg	1500–1800	5.36%	0.27	0.67	0.82	Hanauer [9]
Vienna	1526–1800	17%	0.23	0.55	0.69	Pribram [10]
Wels	1501–1768	17.52%	0.24	0.42	0.68	Pribram [10]
<i>Oats (6 series)</i>						
Augsburg	1500–1800	1.67%	0.21	0.60	0.65	Elsas [3]
Paris	1528–1788	0.37%	0.26	0.40	0.68	Hoffman [8]
Pisa	1553–1800	6.07%	0.16	0.31	0.62	Malanima [11]
Southern England	1500–1702	2.48%	0.19	0.56	0.90	Rogers [5]
Speyer	1517–1799	31.21%	0.25	0.59	0.63	Elsas [3]
Strasbourg	1500–1800	9.33%	0.19	0.66	0.87	Hanauer [9]
<i>Rye (20 series)</i>						
Aachen	1531–1800	12.27%	0.40	0.37	0.51	Rahlf [12]
Augsburg	1500–1800	4.33%	0.40	0.50	0.77	Elsas [3]
Basle	1501–1797	23.31%	0.36	0.60	0.84	Hanauer [9]
Brussels	1575–1795	—	0.38	0.46	0.67	Jacks [13]
Coimbra	1517–1800	14.34%	0.53	0.42	0.57	Palma and Reis [4]
Cologne	1531–1797	0.75%	0.42	0.36	0.71	Metz [14]
Düren	1570–1783	—	0.44	0.32	0.57	Rahlf [12]
Frankfurt	1500–1800	41.31%	0.36	0.48	0.58	Elsas [3]
Gdansk	1538–1800	3.67%	0.28	0.41	0.75	Furtak [6], Pelc [15]
Ghent	1500–1795	—	0.51	0.57	0.73	Jacks [13]
Grenoble	1501–1781	1.69%	0.43	0.50	0.67	Hauser [16]
Leipzig	1572–1800	7.09%	0.35	0.47	0.51	Elsas [3]
Munich	1500–1773	17.60%	0.35	0.52	0.70	Elsas [3]
Paris	1520–1788	6.72%	0.39	0.64	0.43	Hoffman [8]
Pisa	1550–1800	2.61%	0.32	0.77	0.73	Malanima [11]
Speyer	1516–1800	22.40%	0.33	0.39	0.61	Elsas [3]
Strasbourg	1500–1800	4.23%	0.34	0.50	0.76	Hanauer [9]
Toulouse	1512–1792	0.67%	0.35	0.45	0.70	Frêche and Frêche [17]
Würzburg	1500–1799	7.86%	0.38	0.49	0.71	Elsas [3]
Xanten	1500–1800	—	0.31	0.46	0.70	Rahlf [12]
<i>Wheat (32 series)</i>						
Amsterdam	1500–1800	14.00%	0.56	0.34	0.74	Allen and Unger [18]

Table S1: Continued on next page

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City	Coverage	Gaps	Mean price	CV	ARI	Reference(s)
Angers	1580–1789	—	0.56	0.37	0.66	Hauser [16]
Arnhem	1568–1800	—	0.66	0.33	0.66	Verrijn Stuart [19]
Avignon	1570–1789	0.46%	0.86	0.27	0.66	Baehrel [20]
Barcelona	1501–1800	3.01%	0.83	0.34	0.84	Feliu [21]
Bassano del Grappa	1501–1800	21.07%	0.89	0.36	0.73	Lombardini [22]
Brussels	1501–1796	2.71%	0.57	0.50	0.83	Jacks [13]
Cambridge	1500–1799	3.39%	0.55	0.57	0.70	Jacks [13]
Coimbra	1504–1800	12.71%	0.82	0.35	0.67	Palma and Reis [4]
Cologne	1531–1796	4.73%	0.49	0.25	0.74	Ebeling and Irsigler [23]
Douai	1500–1800	0.75%	0.45	0.68	0.73	Hauser [16]
Évora	1506–1800	21.67%	0.77	0.39	0.59	Palma and Reis [4]
Exeter	1500–1800	8.84%	0.64	0.48	0.79	Mitchell [24]
Grenoble	1501–1800	2.00%	0.60	0.45	0.73	Hauser [16]
Leiden	1500–1792	23.41%	0.69	0.35	0.77	Posthumus [25]
Leipzig	1564–1800	3.42%	0.44	0.44	0.65	Elsas [3]
Lisbon	1500–1800	36.11%	0.85	0.43	0.59	Palma and Reis [4]
London	1500–1800	—	0.63	0.56	0.78	Rogers [5]
Madrid	1501–1799	8.67%	0.68	0.50	0.79	Hamilton [7]
Naples	1500–1800	10.60%	0.61	0.37	0.65	Faraglia [26]
Oxford	1559–1799	—	0.68	0.38	0.65	Jacks [13]
Paris	—	2.50%	0.66	0.53	0.79	Hoffman [8]
Pisa	1548–1800	2.00%	0.43	0.33	0.71	Malanima [11]
Siena	1546–1765	—	0.69	0.34	0.74	Parenti [27]
Strasbourg	1500–1800	5.00%	0.48	0.61	0.79	Hanauer [9]
Toulouse	1500–1792	—	0.53	0.44	0.76	Frêche and Frêche [17]
Tours	1500–1788	2.74%	0.70	0.52	0.77	Hauser [16]
Utrecht	1500–1800	12.00%	0.57	0.33	0.78	Sillem [28]
Valencia	1500–1789	0.67%	0.94	0.37	0.91	Hamilton [29]
Vienna	1531–1800	21.80%	0.41	0.61	0.74	Pribram [10]
Würzburg	1500–1799	28.33%	0.48	0.49	0.64	Elsas [3]
Zürich	1540–1800	—	0.80	0.48	0.61	Studer [30]

Table S1: It ends from the previous page.

Table S2: Grain harvest records, including tithe, yield ratio and yield per unit records, with information about location, period covered, grain types, and reference(s). Abbreviations as follows for the grain types: B = barley; R = rye; O = oats; W = wheat; S = spelt; M = maize; Ri = Rice; B/R = barley/rye mixture; R/W = rye/wheat mixture.

Location	Period	Record Type	Grain Type(s)	Reference(s)
<i>Denmark</i>				
Zealand	1610–1659	Yield ratio	B, R	Olsen [31]
<i>France</i>				
Provence	1731–1788	Yield ratio	Mixed	Goy [32]
Agde	1593–1734	Tithe	Mixed	Ladurie [33]
Strasbourg	1484–1790	Tithe	Mixed	Veyrassat-Herren [34]
Beaume	1597–1788	Tithe	Mixed	Goy [35]
Beziers	1560–1764	Tithe	Mixed	Ladurie [33]
Cambresis	1402–1599	Tithe	O, W	Neveux [36]
St Trophime	1662–1788	Tithe	W	Goy [32]
Burgundy	1509–1788	Tithe	Mixed	Silbert [37]
<i>Hungary</i>				
Sopron	1429–1630	Tithe	Mixed	Hunyadi [38]
<i>Italy</i>				
Piemonte	1746–1797	Yield per unit	B, R, Ri, M, O, W	Davico [39]
Siena	1546–1667	Yield per unit	Mixed	Parenti [27]
<i>Luxembourg</i>				
Grevenmacher	1444–1680	Tithe	Mixed	Yante [40]
Remich	1444–1746	Tithe	Mixed	Yante [40]
<i>Spain</i>				
Mondoñedo	1595–1800	Tithe	Mixed	Eiras Roel [41]
Santiago	1606–1799	Tithe	Mixed	Eiras Roel [41]
Galice	1595–1800	Tithe	Mixed	Eiras Roel [41]
Orense	1598–1800	Tithe	Mixed	Eiras Roel [41]
Aragon	1660–1827	Tithe	W	Ciria [42]
Guadalajara	1700–1800	Tithe	B, R, O, W	Santiago-Caballero [43]
Calañas	1563–1835	Tithe	W	Ponsot [44]
Puebla de Guzman	1563–1835	Tithe	W	Ponsot [44]
Lucena	1563–1835	Tithe	W	Ponsot [44]
Bollullos	1563–1835	Tithe	W	Ponsot [44]
El Rincón farm	1699–1781	Yield ratio	W	Llopis et al. [45]
La Burguilla farm	1699–1781	Yield ratio	W	Llopis et al. [45]
Madrigalejo farm	1699–1781	Yield ratio	W	Llopis et al. [45]
La Vega farm	1699–1781	Yield ratio	W	Llopis et al. [45]
Quintanajuar farm	1699–1781	Yield ratio	W	Llopis et al. [45]
Panguia farm ^a	1695–1799	Yield per unit	W	Llopis et al. [45]
Farms of Matallana	1699–1781	Yield ratio	W	Llopis et al. [45]
Rinconada Alta farm ^a	1695–1799	Yield per unit	W	Llopis et al. [45]
Andalusia ^a	1616–1800	Yield per unit	B, W	Ponsot [46]

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Location	Period	Record Type	Grain Type(s)	Source(s)
Cortijo Pan Ximenez, Andalusia	1611–1800	Yield ratio	B, W	Ponsot [46]
El Alto Mijares	1680–1800	Tithe	Mixed	Ardit Lucas [47]
El Camp de Morvedre	1680–1800	Tithe	Mixed	Ardit Lucas [47]
El Camp de Túria	1680–1800	Tithe	Mixed	Ardit Lucas [47]
El Comtat	1680–1800	Tithe	Mixed	Ardit Lucas [47]
El Valle de Cofrentes	1680–1800	Tithe	Mixed	Ardit Lucas [47]
L'Alcoià	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Canal de Navarrés	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Costera	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Hoya de Buñol	1680–1800	Tithe	Mixed	Ardit Lucas [47]
L'Horta	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Marina Alta	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Marina Baixa	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Safor	1680–1800	Tithe	Mixed	Ardit Lucas [47]
La Vall d'Albaida	1680–1800	Tithe	Mixed	Ardit Lucas [47]
Les Riberes	1680–1800	Tithe	Mixed	Ardit Lucas [47]
Los Serranos	1680–1800	Tithe	Mixed	Ardit Lucas [47]
País Valencià	1680–1800	Tithe	Mixed	Ardit Lucas [47]
Mallorca	1466–1800	Tithe	B, O, W	Vidal [48]
<i>Sweden</i>				
Härjedalen	1582–1800	Tithe	Mixed	Skoglund [49]
Jämtland	1565–1800	Tithe	Mixed	Skoglund [49]
Kopparberg County	1572–1740	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Örebro County	1665–1720	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Östergötland County	1573–1680	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Södermanland County	1572–1681	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Stockholm County	1572–1730	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Uppsala County	1572–1740	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Värmland County	1575–1730	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
Västmanland County	1572–1740	Tithe	B/R, O, W	Leijonhufvud [50], Hallberg et al. [51]
<i>Switzerland</i>				
Burgdorf	1550–1825	Tithe	R/W	Pfister [52]
Cappelhof	1531–1797	Tithe	R/W	Pfister [52]
Fraumünsteramt	1531–1797	Tithe	R/W	Pfister [52]
Frienisberg	1529–1797	Tithe	R/W	Pfister [52]
Geneva	1542–1780	Tithe	R/W	Head-Köenig and Veyrassat-Herren [53]
Gottstatt	1558–1825	Tithe	R/W	Pfister [52]
Königsfelden	1556–1797	Tithe	R/W	Pfister [52]
Köniz	1732–1825	Tithe	R/W	Pfister [52]
Lausanne	1538–1796	Tithe	R/W	Pfister [52]
Moudon	1564–1796	Tithe	R/W	Pfister [52]
Nidau	1535–1800	Tithe	R/W	Pfister [52]
Romainmôtier	1538–1796	Tithe	R/W	Pfister [52]
Spital	1700–1797	Tithe	R/W	Pfister [52]
Stift Bern	1529–1796	Tithe	R/W	Pfister [52]
Töss	1529–1797	Tithe	R/W	Pfister [52]
Trachselwald	1534–1797	Tithe	R/W	Pfister [52]
Wädenswil	1533–1797	Tithe	R/W	Pfister [52]
Wangen	1686–1800	Tithe	R/W	Pfister [52]

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Table S2 – Continued from previous page

Location	Period	Record Type	Grain Type(s)	Source(s)
Zofingen	1542–1797	Tithe	R/W	Pfister [52]
Basel	1500–1800	Yield ratio	R, S	Head-Köenig [54]
St. Gallen	1549–1799	Yield ratio	S	Head-Köenig [54]
Zurich	1501–1800	Yield ratio	R, S	Head-Köenig [54]
Winterthur	1536–1785	Yield ratio	R, S	Head-Köenig [54]

Table S3: Summary Statistics of Famine Episodes

	Region	mean	sd	min	max	N
duration	Central Europe	3.23	1.41	1.00	6.00	22
	France	2.44	1.62	1.00	6.00	18
	Great Britain	2.80	0.79	1.00	4.00	10
	Ireland	3.56	3.36	1.00	12.00	9
	Italy	3.13	2.01	1.00	11.00	23
	Low Countries	2.50	0.65	2.00	4.00	14
	Nordic Countries	3.18	1.62	1.00	8.00	22
	Russia/Ukraine	2.14	1.56	1.00	5.00	21
	Spain	3.29	1.90	1.00	8.00	21

S2 Summary Statistics and Spatial Coverage

We present here summary tables of our datasets for famine duration, grain harvests, grain prices, and fish prices. We show the spatial coverage of the harvest and price data in Figure S1.

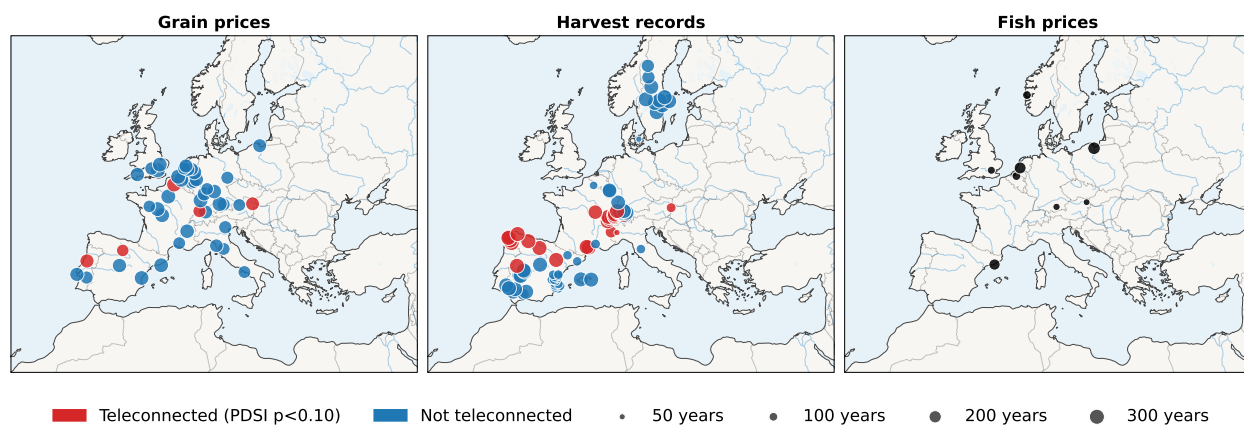


Figure S1: Spatial Coverage of Grain and Fish Prices and Harvest Series.

We also detail the composition and data extend of each region in Table S8.

Table S4: Summary Statistics for Grain Price Data

	Mean	SD	Min	Max	N
Price	0.54	0.31	0.04	3.99	11344
NINO3.4	0.05	0.67	−1.95	2.17	11344
PDSI	−0.22	1.48	−6.73	5.17	11344
JSL	−0.53	2.03	−5.37	6.61	11344
NAO_cal	−0.10	0.50	−1.43	1.23	11344
temp AMJJ	−0.15	0.60	−2.42	2.58	11344
temp NDJF	−0.22	0.77	−3.45	2.69	11344
precip AMJJ	0.97	9.34	−54.48	39.61	11344
precip NDJF	1.37	12.42	−82.20	68.30	11344
ongoing wars	6.90	3.99	0.00	18.00	11344
Deaths	69 916.78	103 485.59	0.00	446 412.37	11344

Table S5: Summary Statistics for Grain Tithes Data

	Mean	SD	Min	Max	N
logyield	6.39	2.43	0.14	13.66	14915
NINO3.4	0.07	0.69	−1.95	2.17	14915
PDSI	−0.19	1.44	−6.55	4.66	14915
JSL	−0.53	2.07	−5.37	6.61	14915
NAO_cal	−0.09	0.51	−1.43	1.23	14915
temp AMJJ	−0.18	0.61	−2.42	2.58	14915
temp NDJF	−0.20	0.75	−3.38	2.81	14915
precip AMJJ	2.27	9.76	−54.48	40.77	14915
precip NDJF	3.42	13.48	−87.25	68.30	14915
ongoing wars	6.29	3.96	0.00	18.00	14915
Deaths	71 844.89	99 212.10	0.00	446 412.37	14915

Table S6: Summary Statistics for Grain Yields Data

	Mean	SD	Min	Max	N
logyield	3.08	3.29	−3.22	14.74	3934
NINO3.4	0.06	0.70	−1.95	2.17	3934
PDSI	−0.19	1.47	−6.73	4.30	3934
JSL	−0.32	2.10	−5.37	6.61	3934
NAO_cal	−0.07	0.50	−1.43	1.23	3934
temp AMJJ	−0.22	0.65	−2.42	2.58	3934
temp NDJF	−0.34	0.72	−3.38	2.17	3934
precip AMJJ	3.12	10.45	−47.83	39.61	3934
precip NDJF	4.06	14.37	−69.30	65.24	3934
ongoing wars	5.72	3.97	0.00	18.00	3934
Deaths	75 013.27	102 854.78	0.00	446 412.37	3934

Table S7: Summary Statistics for Fish Prices Data

	Mean	SD	Min	Max	N
Price	42.99	59.25	0.00	353.00	990
NINO3.4	0.06	0.65	−1.95	2.17	990
PDSI	−0.23	1.36	−4.40	5.10	990
JSL	−0.67	1.96	−5.37	6.61	990
NAO_cal	−0.13	0.49	−1.43	1.23	990
temp AMJJ	−0.14	0.48	−2.03	1.73	990
temp NDJF	0.06	0.88	−3.64	2.34	990
precip AMJJ	1.92	7.41	−23.91	25.33	990
precip NDJF	4.35	9.75	−38.86	38.04	990
ongoing wars	7.03	3.89	0.00	18.00	990
Deaths	56 861.89	91 182.36	0.00	446 412.37	990

Table S8: Data coverage by famine region and country (1500–1800). Locs = distinct geographic locations; TC = teleconnected to ENSO (PDSI $p < 0.10$); Years = earliest–latest observation. Famine years are at the region level.

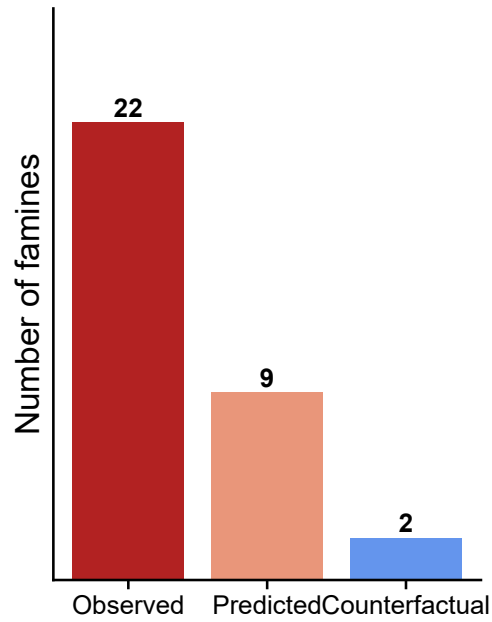
Region	Country	Fam. yrs	Grain price			Yield		
			Locs	TC	Years	Locs	TC	Years
Central Europe	Austria	71	2	1	1501–1800	—	—	—
	Germany		10	0	1500–1800	—	—	—
	Hungary		—	—	—	1	1	1500–1630
	Poland		1	0	1501–1800	—	—	—
	Switzerland		2	1	1501–1800	23	15	1500–1800
France	France	44	8	1	1500–1800	7	4	1500–1800
Great Britain	England	28	4	0	1500–1800	—	—	—
Ireland	—	32	—	—	—	—	—	—
Italy	Italy	72	4	0	1501–1800	3	2	1546–1797
Low Countries	Belgium	35	2	0	1500–1796	—	—	—
	Luxembourg		—	—	—	2	0	1500–1786
	Netherlands		4	0	1500–1800	—	—	—
Nordic Countries	Denmark	70	—	—	—	1	0	1610–1659
	Sweden		—	—	—	10	0	1500–1800
Russia/Ukraine	—	45	—	—	—	—	—	—
Spain	Portugal	69	3	1	1500–1800	—	—	—
	Spain		4	1	1500–1800	38	9	1500–1800

S3 ENSO and the Onset of Famine periods

Machine Learning Attribution We report the estimated attribution of famine onsets in Central Europe using increasing subsets of predictors. For each specification, we present (A) observed and counterfactual famine onsets, (B) permutation feature importance, and (C) model performance.

We report additional performance metrics for the main classifier in the figure below. The cross-validated out-of-sample performance is affected by class imbalance, which is inherent to the rarity of famine onset events in the historical record. While this limits predictive performance in a strict forecasting sense, our primary objective is not prediction but causal attribution. In this context, the model’s ability to recover meaningful in-sample relationships is more relevant than its extrapolation performance.

(a) Observed vs. counterfactual



(b) Performance

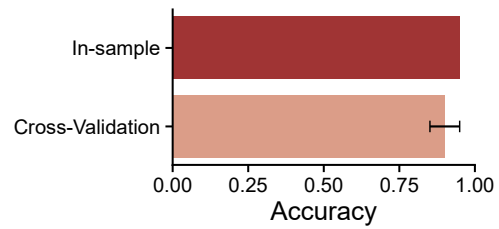
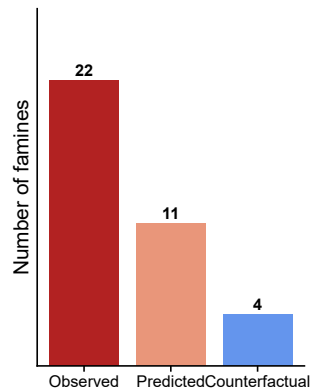
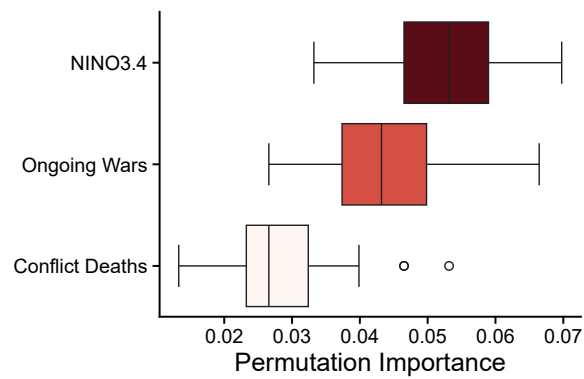


Figure S2: Attribution with NINO3.4 only.

(a) Observed vs. counterfactual



(b) Feature importance



(c) Performance

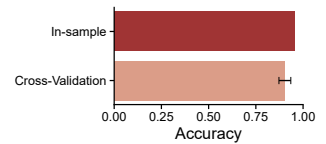


Figure S3: Attribution with NINO3.4, ongoing wars, and conflict deaths.

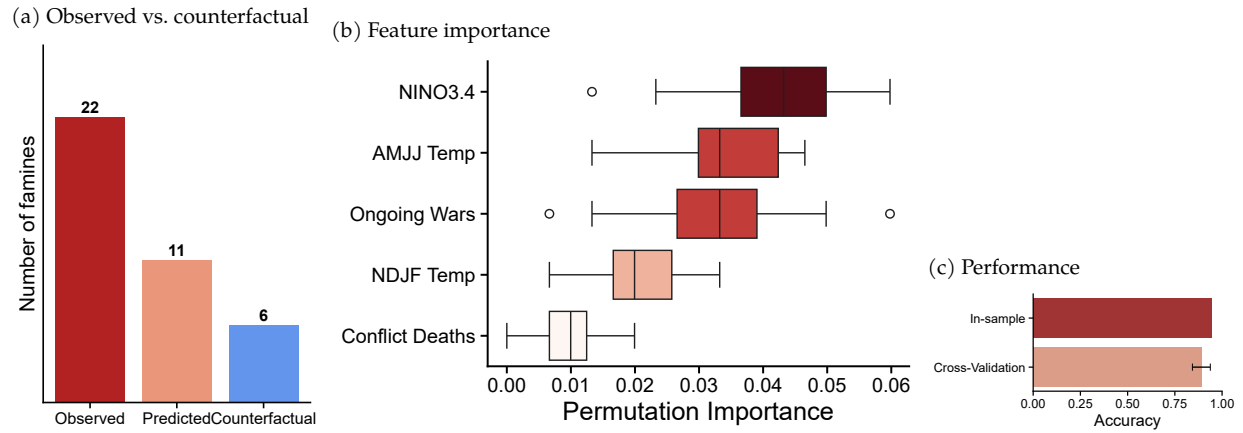


Figure S4: Attribution with NINO3.4, ongoing wars, estimated conflict deaths, NDJF and AMJJ temperatures.

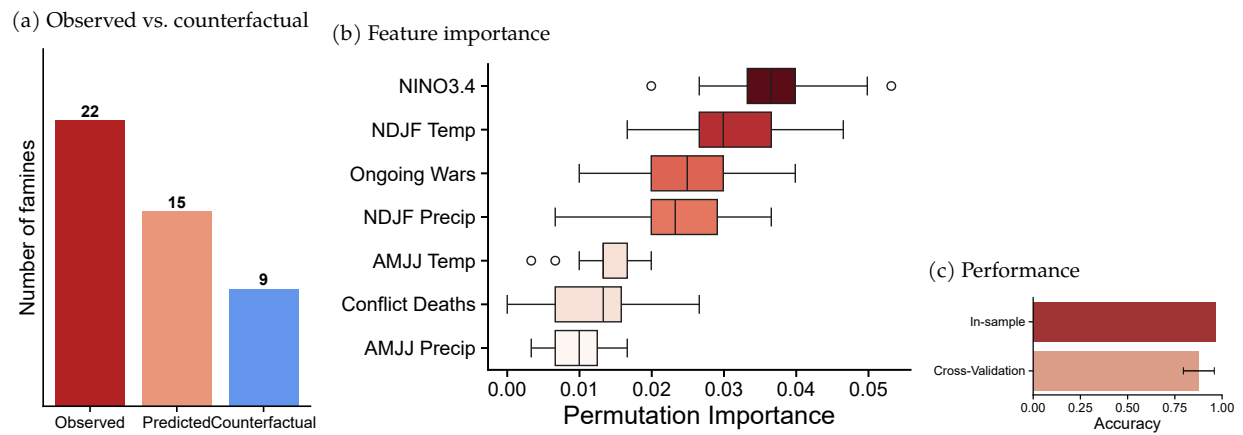


Figure S5: Attribution with NINO3.4, ongoing wars, estimated conflict deaths, NDJF and AMJJ temperatures, NDJF precipitation.

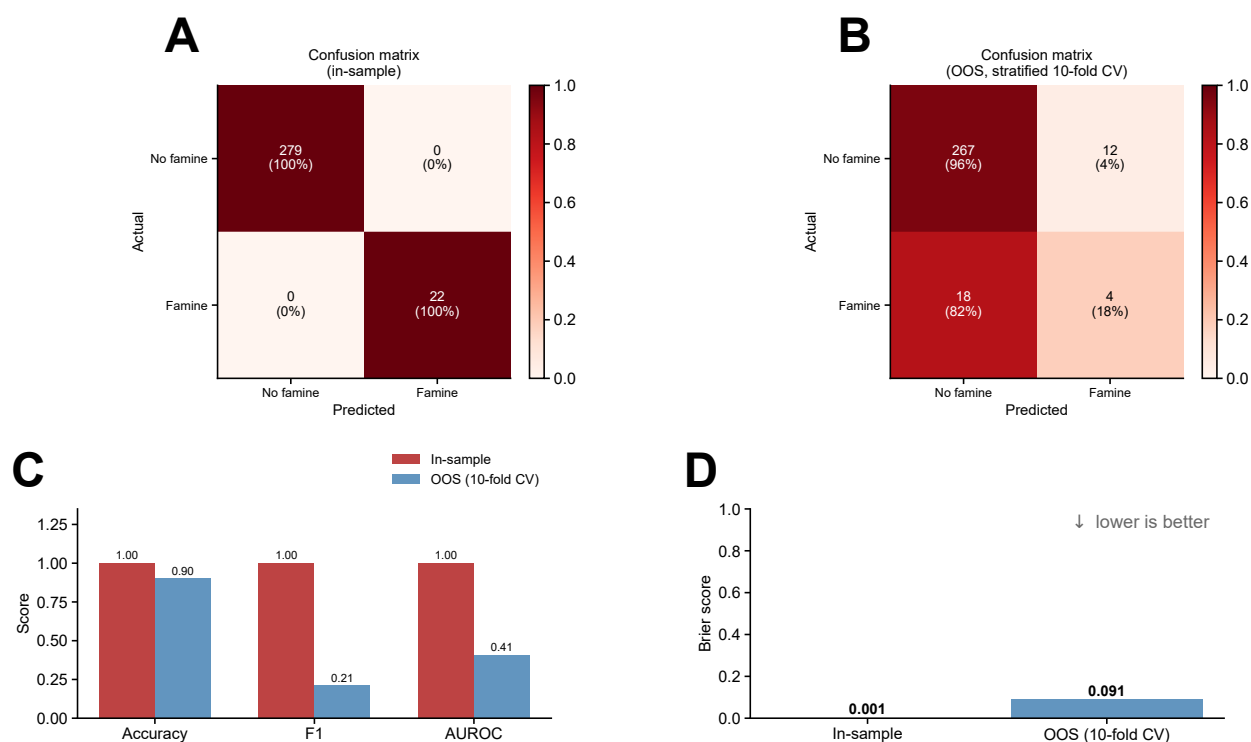


Figure S6: In-sample and out-of-sample performance of the all-features gradient boosting classifier for famine onset. (A) Confusion matrix evaluated on the full training sample (in-sample). Cells show the count and row-normalized share of observations classified into each predicted/actual category. (B) Confusion matrix evaluated via 10-fold cross-validation (out-of-sample); predicted probabilities are obtained by averaging predictions from held-out folds and thresholded at 0.5. (C) Classification metrics for the in-sample (red) and out-of-sample (blue) evaluations: Accuracy (share of correctly classified observations), F1 score (harmonic mean of Precision–positive predictive value–and Recall–sensitivity/true positive rate), AUC (area under the receiver operating characteristic curve), and (D) the Brier score (mean squared difference between predicted probabilities and actual binary outcomes). The all-features model includes NINO3.4, conflict deaths, ongoing wars, NDJF temperature, AMJJ temperature and precipitation, and the self-calibrating Palmer Drought Severity Index (scPDSI) as predictors.

S4 Assessing ENSO Teleconnections to the Early Modern European Climate

We explore potential teleconnections between the ENSO index (NINO3.4) and our primary climate variables by calculating the grid-wise Pearson correlation between each pixel's time series in the climate reconstructions and the ENSO time series. Our results show that June–August soil moisture, and to a lesser extent, April–July precipitation, are the only variables significantly influenced by ENSO. This finding motivates our use of the self-calibrating Palmer Drought Severity Index (scPDSI) to classify a location's level of ENSO teleconnection.

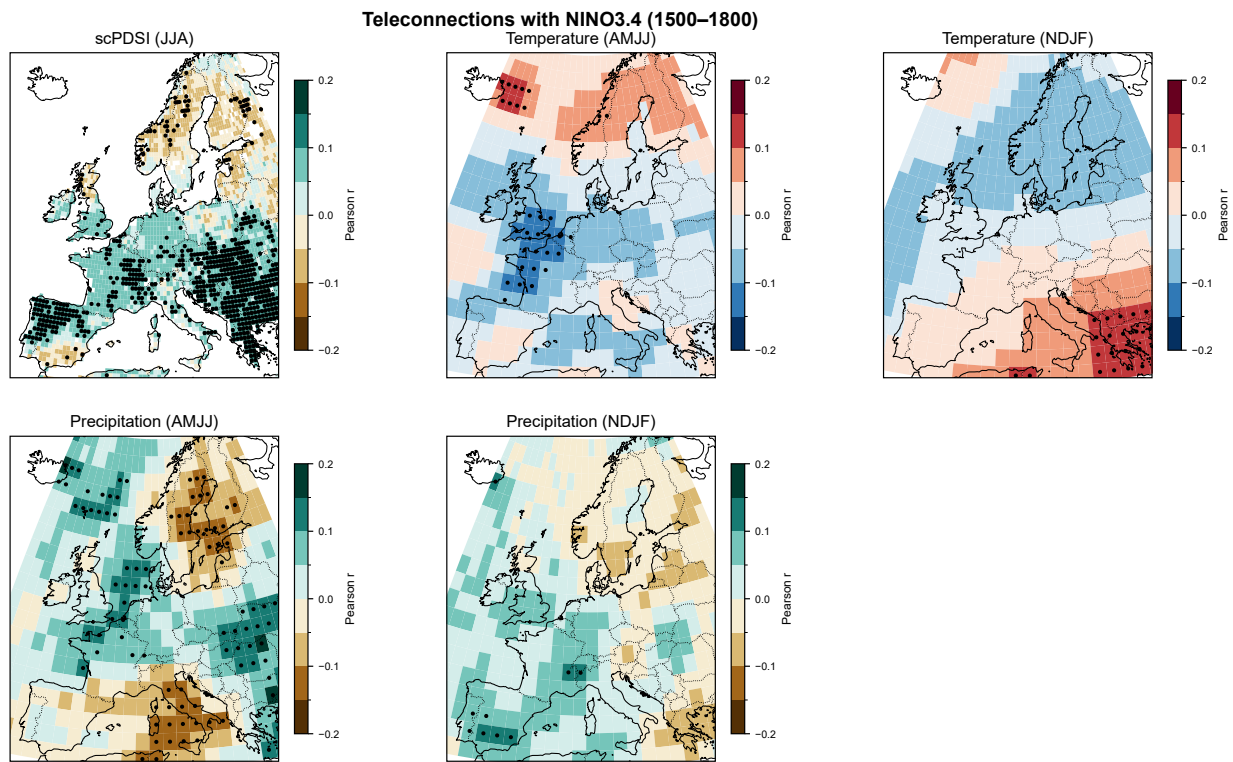


Figure S7: ENSO–climate correlation maps. Dotted cells mark significant ($p < 0.1$) correlations.

S5 Impact of ENSO on Harvests under Different Teleconnection Partitions

The main section presents the effect of a positive ENSO shock on harvests according to a teleconnection partition that uses soil moisture (scPDSI). Here we show additional results when using April–July precipitation to assess ENSO teleconnections. We obtain stronger results to the scPDSI-based partitioning when using AMJJ precipitation data for harvests, albeit with wider standard errors.

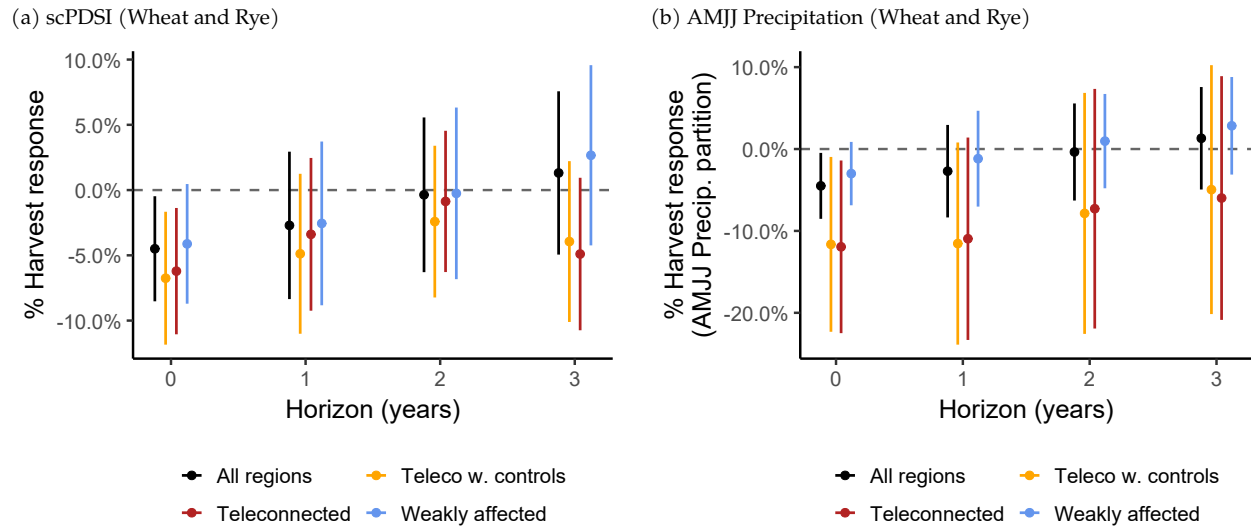


Figure S8: **Impulse responses to ENSO shocks for grain harvests** Each panel shows the impulse responses of a 1 °C ENSO shock on inter-annual variability in grain harvest records, while holding other factors constant. Teleconnection status is granted to locations whose local climate is significantly correlated at the 10% level to ENSO.

S6 Regional Heterogeneity in the Survival Analyses

We examine potential regional heterogeneity in the response to ENSO by including interaction terms between the NINO3.4 index and dummy region variables within a time-dependent Cox proportional hazards model. Additionally, we account for regional differences in baseline hazard functions through stratification by region. The results in S10 show an interesting tendency of Ireland to be more vulnerable to La Niña events (cooler NINO3.4 temperatures) than El Niño events.

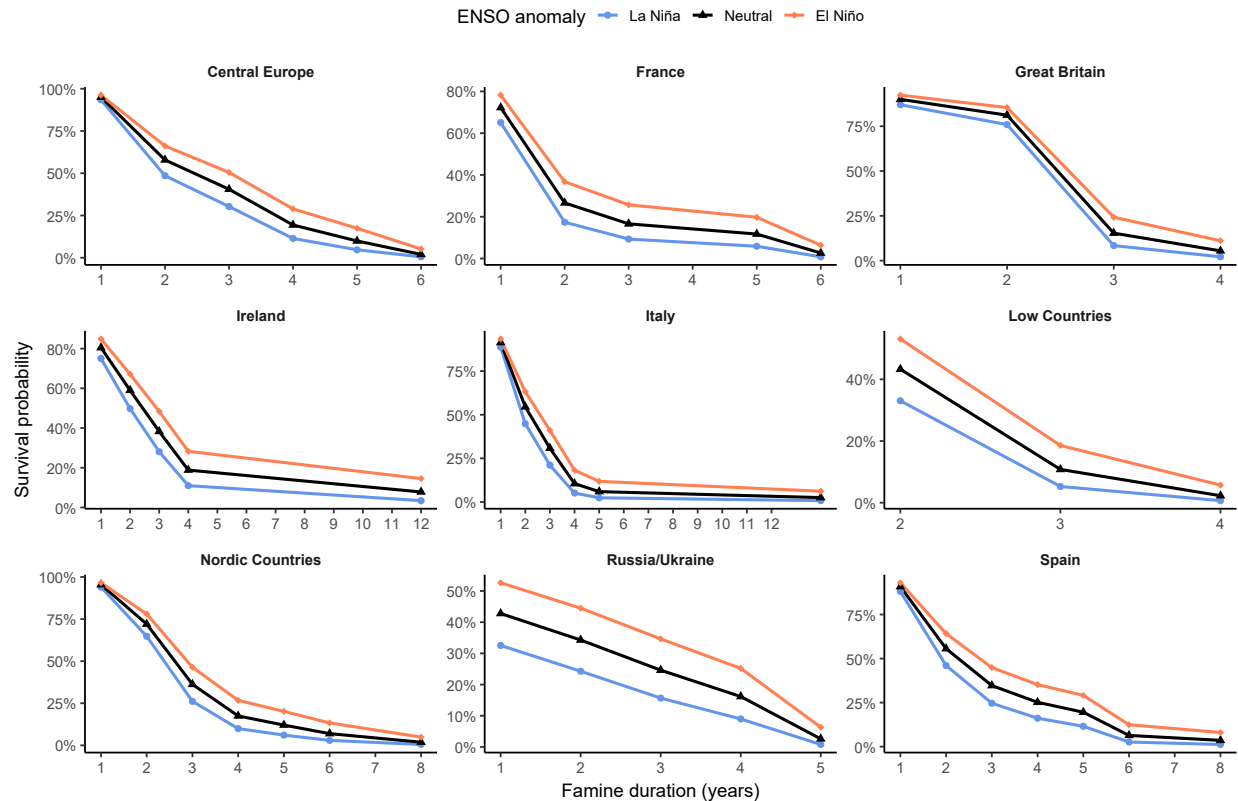


Figure S9: Survival Curves from Cox Regression with Region stratification.

We also report the results of our time-varying Cox Regression from the main section in Table S9.

Survival by Region × ENSO (interaction model)

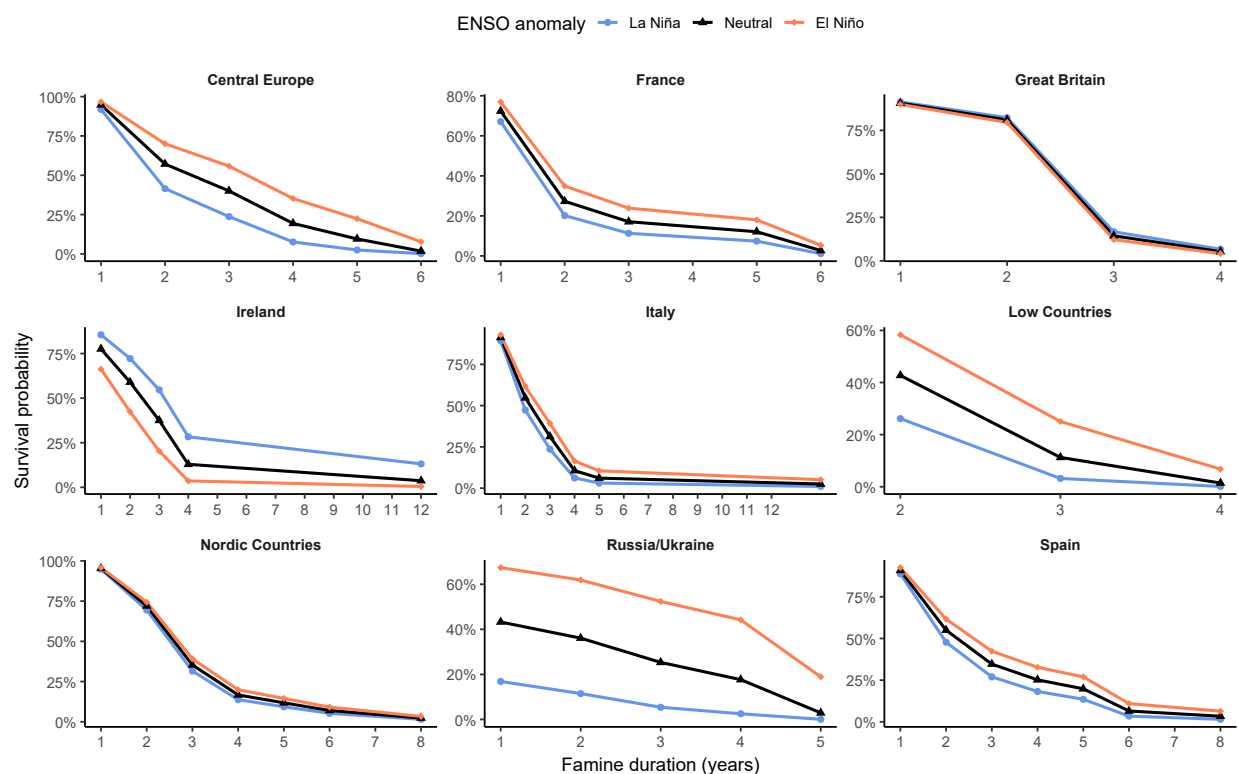


Figure S10: Survival Curves from Cox Regression with Region stratification and Region interaction for the ENSO hazard estimate.

Table S9: Log Hazard Ratio of Nino 3.4 on Famine Duration, Time-varying Cox Model

	(1)	(2)	(3)	(4)	(5)	(6)
nino34	-0.260** (0.124)	-0.279** (0.140)	-0.279** (0.140)	-0.260** (0.124)	-0.272** (0.129)	-0.305** (0.145)
Clustered SEs	No	No	Yes	No	Yes	No
Strata by Region	No	Yes	Yes	No	No	Yes
Controls	No	No	No	No	Yes	Yes
Random Effects	No	No	No	Yes	No	No
Proportional Hazards p	0.939	0.648	0.648	-	0.976	0.549
Concordance Index	0.558	0.566	0.566	0.558	0.559	0.577
AIC	1288.2	643.1	643.1	1288.2	1294.0	649.0
BIC	1291.3	646.1	646.1	1291.3	1309.3	664.3

* p < 0.1, ** p < 0.05, *** p < 0.01

S7 Machine Learning Survival Analyses

We demonstrate that ENSO, measured by the NINO3.4 index, possesses predictive power in modeling famine hazard. As outlined in the main text, cross-validation exercises highlight ENSO’s explanatory power (see Figure 4). We further show that when models are overfit to the full sample, ENSO consistently emerges as a key predictor (see Figure S11).

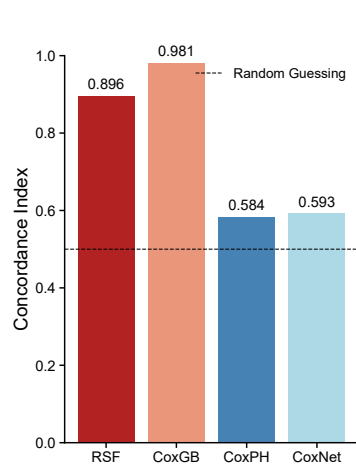
We use the following hyper-parameters for the full-sample models:

1. **Random Survival Forest (RSF)**: Number of trees: 200; Maximum depth of each tree: 20
2. **Gradient Boosting Survival Analysis (GBSA)**: Number of boosting iterations: 200; Maximum depth of each tree: 3; Learning rate: 0.1
3. **Elastic-Net Cox (Coxnet)**: Regularization parameter α : 0.1; L1 ratio (Elastic-net mixing): 0.5; Maximum number of iterations: 10,000

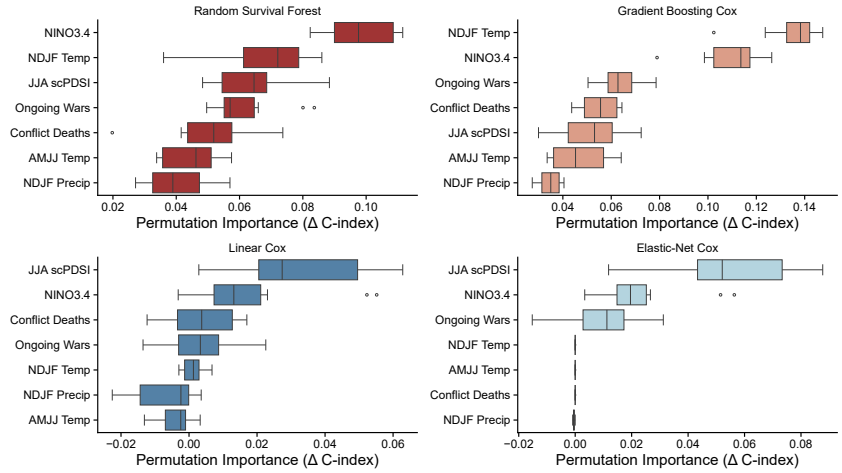
The grids used for cross-validation tuning are described in table S10.

Table S10: Hyperparameter grids used for model tuning via cross-validation.

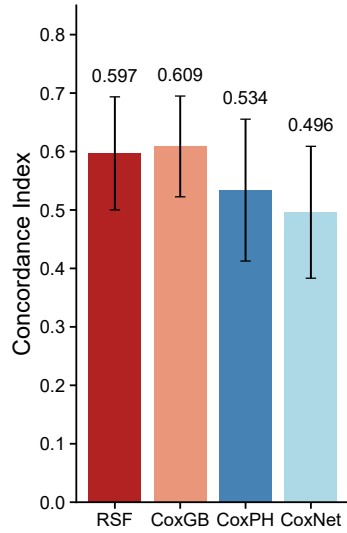
Model	Hyperparameters
CoxNet (CoxPH with ElasticNet)	$\text{alphas} \in \{0.001, 0.01, 0.1, 1, 10\}$ $\text{l1_ratio} \in \{0.01, 0.5, 1.0\}$
Random Survival Forest (RSF)	$\text{n_estimators} \in \{10, 20, 50\}$ $\text{min_samples_split} \in \{3, 5, 10\}$ $\text{min_samples_leaf} \in \{3, 5, 10\}$ $\text{max_features} \in \{\sqrt{\cdot}, 0.5\}$
Gradient Boosting Survival Analysis (GBSA)	$\text{n_estimators} \in \{10, 20, 50\}$ $\text{learning_rate} \in \{0.1, 0.5, 0.9\}$ $\text{max_depth} \in \{1, 3, 5\}$



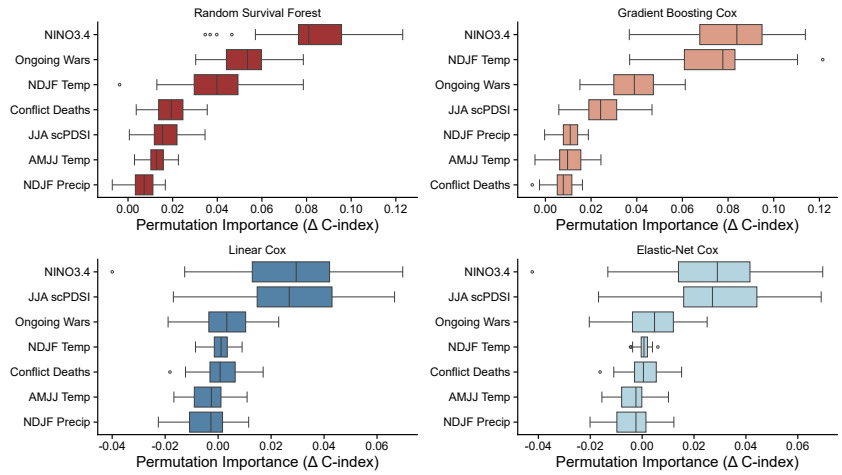
(a) CI (full sample)



(b) Feature importance (full sample)



(c) CI (CV)



(d) Feature importance (CV)

Figure S11: Model Performance and Feature Importance in Predicting Famine Duration Model performance (concordance index, CI) and feature importance on the full sample and test set from each fine-tuned survival models – Random Survival Forest (RSF), Gradient Boosting Cox (CoxGB), standard Cox Proportional Hazards (CoxPH), and Cox regression with elastic net regularization (CoxNet). Panels (a) and (b) show full-sample results; panels (c) and (d) report out-of-sample results using nested cross-validation (CV) with error bars based on the 10 outer cross validation folds. Across both setups, the ENSO index consistently emerges as a key predictor of famine duration.

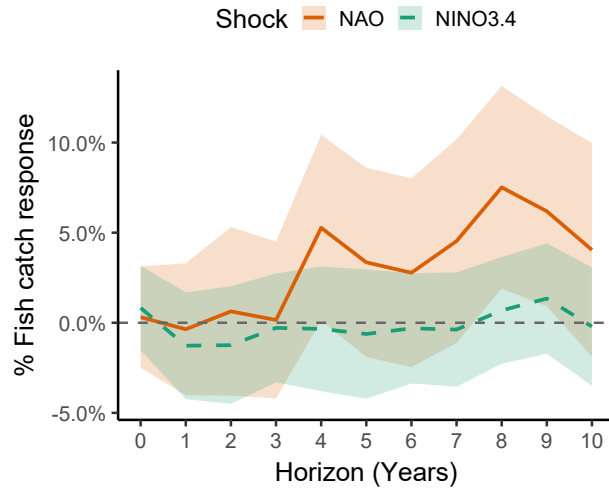


Figure S12: Impulse Responses of a 1 °C NINO3.4 shock and a 1 unit NAO shock on Fish Catches. Shaded area represents the 95% confidence interval from Driscoll-Kraay standard errors.

S8 Null Effect of ENSO on Fish Catches

We use a compilation of fish catches of North Atlantic cod and herring spanning 1520–1790. The data on fish catches are published in Holm et al. [55] with supporting documentation published by Nicholls et al. [56].

Using a panel local projection with city-species and decade fixed-effects, we report a null effect of ENSO on fish catches for the early modern period in Figure S12, consistent with similar findings for the present day [57]. We use both the NINO3.4 index, and the North Atlantic Oscillation (NAO)¹, known for its connection to ENSO patterns [59] and its influence on marine ecosystems [60].

¹using the calibrated reconstruction from [58]

S9 Robustness Checks

We conduct an extensive battery of robustness checks for our main analyses, detailed below. Find their summary in Table S11.

Table S11: Summary of robustness checks.

Category	Robustness Checks
Data quality	Alternative grain price datasets: Federico et al. [61] and Allen [62] (S9.2). Alternative harvest datasets: Slicher van Bath [63] compilation (S9.2).
Model specification	Parametric survival models (S9.1.1). Distributed-lag FE regressions: famine duration, prices, harvests (S9.1.2). Nonlinearity: allow for nonlinear ENSO effects (S9.1.3).
Sample composition	Leave-one-out: drop each location or famine episode (S9.4). Time-block exclusion: remove 20-year windows (S9.5).
Inference	Alternative standard errors: Conley, Spatial HAC, two-way clustering (S9.6).
Identification of a Causal Effect	Control for decade and location fixed effects, as well as time- and location-varying controls (throughout Main and Supplementary S9). Placebo/permutation tests: permute ENSO across and within locations (S9.3).
Endogeneity	Granger causality test on time series: prices/harvests do not Granger-cause ENSO anomalies (S9.7).

S9.1 Alternative Model Specifications

We report results under alternative model specification for the famine duration analyses, as well as the impact of the ENSO on prices and harvests.

S9.1.1 Parametric Survival Models

We use parametric survival models with 3 distributions that enable use to use Region stratification, Weibull, log-logistic and Gaussian (Tobit model). Across all three choices of parametric modeling, we find that ENSO is significantly associated with longer famine periods.

Table S12: Parametric Survival Models of Famine Duration

	<i>Dependent variable:</i>		
	Duration		
	<i>Weibull</i>	<i>survreg: loglogistic</i>	<i>Tobit</i>
	(1)	(2)	(3)
Nino34	0.205* (0.121)	0.231** (0.094)	0.485* (0.270)
Constant	1.126*** (0.042)	0.927*** (0.040)	2.706*** (0.116)
Observations	160	160	
Log Likelihood	−276.507	−267.186	−295.544
χ^2 (df = 1)	2.946*	5.559**	3.156*

Note:

*p<0.1; **p<0.05; ***p<0.01

S9.1.2 Distributed Lags Fixed Effects Regressions

As an alternative to estimate the causal effect of the El Niño-Southern Oscillation (ENSO) on famine duration, grain harvests and prices, we employ a fixed-effects regression model with distributed lags. We model our variable of interest as a function of both contemporaneous and lagged values (up to three years) of the ENSO shock.

The estimating equations are given by:

$$\ln(\text{GrainPrice}_{i,t}) = \sum_{l=0}^3 \beta_l^G \text{ENSO}_{t-l} + \alpha_i^G + \gamma_{\text{Decade}(t)}^G + \theta_i^G t + \epsilon_{i,t}^G, \quad (\text{S1})$$

$$\ln(\text{FishPrice}_{i,s,t}) = \sum_{l=0}^3 \beta_l^F \text{ENSO}_{t-l} + \alpha_{i,s}^F + \gamma_{\text{Decade}(t)}^F + \theta_i^F t + \epsilon_{i,s,t}^F, \quad (\text{S2})$$

$$\ln(\text{GrainHarvest}_{i,g,r,t}) = \sum_{l=0}^3 \beta_l^Y \text{ENSO}_{t-l} + \alpha_{i,g,r}^Y + \gamma_{\text{Decade}(t)}^Y + \theta_i^Y t + \epsilon_{i,g,t}^Y, \quad (\text{S3})$$

$$\text{Duration}_{R,t} = \beta^D \text{ENSO}_t + \alpha_R^D + \gamma_{\text{Decade}(t)}^D + \epsilon_{R,t}^D. \quad (\text{S4})$$

where i indexes locations (cities for prices and estates or districts for harvests), s denotes fish species, g represents grain-type, r harvest record type, and R indexes regions. Each specification includes location-

/location-species/location-grain-record or region-specific fixed effects (α), decade fixed effects (γ), and a linear, location-specific time trend (θ). Because ENSO shocks do not vary by location or commodity, the error terms ϵ may exhibit serial and cross-sectional dependence. For inference, we employ Driscoll–Kraay standard errors [64], which are robust to both forms of dependence.

The resulting regression tables below are in agreement with the main section’s findings. On the one hand we see a strong effect of a ENSO anomalies, both the average NINO3.4 value during the famine and the maximum value during its first two years, on the duration of famines (Tables S13 and S14). On the other hand we estimate a similar impact of a +1 °C ENSO shock on grain prices (6% with a similar lag of 1 year, see Table S15), fish prices (5% with a lag of 3 years, see Table S16), and grain yields (–5% on the scPDSI-teleconnected harvests), see Table S17).

Table S13: Effect of a 1°C Anomaly in the Average Nino 3.4 Index on Famine Duration

Dependent Variable:	Duration (years)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Poisson	Poisson	Neg. Bin.	Neg. Bin.
<i>Variables</i>						
NINO3.4	0.5060*	0.6314**	0.1862**	0.2408**	0.1862**	0.2408**
	(0.2589)	(0.2590)	(0.0940)	(0.0945)	(0.0942)	(0.0948)
Controls	No	Yes	No	Yes	No	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
AIC	638.24	641.87	601.82	606.08	601.82	606.08
BIC	668.99	694.15	632.57	658.35	632.57	658.36
Observations	160	160	160	160	160	160
Squared Correlation	0.07526	0.13331	0.07317	0.14165	0.07317	0.14164

Clustered (Region) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S14: Effect of a 1°C Anomaly in the Max 2-year Nino 3.4 Index on Famine Duration

Dependent Variable:	Duration (years)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Poisson	Poisson	Neg. Bin.	Neg. Bin.
<i>Variables</i>						
Max NINO3.4 (2y)	0.6035** (0.2151)	0.6656** (0.2200)	0.2094*** (0.0806)	0.2386*** (0.0875)	0.2094*** (0.0809)	0.2386*** (0.0878)
Controls	No	Yes	No	Yes	No	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>						
AIC	633.29	636.33	597.18	601.11	597.18	601.11
BIC	664.04	688.61	627.93	653.38	627.93	653.39
Observations	160	160	160	160	160	160
Squared Correlation	0.10344	0.16278	0.09704	0.16748	0.09704	0.16748

Clustered (Region) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S15: Effect of a 1°C Anomaly in the Nino 3.4 Index on Grain Prices

Dependent Variable:	Log Grain Price			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
NINO3.4 T	0.0147 (0.0143)	0.0139 (0.0141)	0.0159 (0.0145)	0.0149 (0.0142)
NINO3.4 T-1	0.0453*** (0.0110)	0.0457*** (0.0110)	0.0445*** (0.0109)	0.0449*** (0.0109)
NINO3.4 T-2	0.0352*** (0.0110)	0.0339*** (0.0111)	0.0358*** (0.0109)	0.0343*** (0.0110)
NINO3.4 T-3	0.0326*** (0.0115)	0.0317*** (0.0112)	0.0325*** (0.0113)	0.0316*** (0.0109)
Decade FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Controls	None	Climate	Conflict	Climate + Conflict
<i>Fit statistics</i>				
Observations	10,278	10,278	10,278	10,278
R ²	0.72151	0.72309	0.72195	0.72335

Driscoll-Kraay (L=4) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S16: Effect of a 1°C Anomaly in the Nino 3.4 Index on Fish Prices

Dependent Variable:	Log Fish Price			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
NINO3.4 T	0.0042 (0.0104)	0.0041 (0.0107)	0.0050 (0.0105)	0.0049 (0.0108)
NINO3.4 T-1	0.0189 (0.0135)	0.0180 (0.0130)	0.0161 (0.0136)	0.0153 (0.0131)
NINO3.4 T-2	0.0117 (0.0098)	0.0104 (0.0099)	0.0107 (0.0097)	0.0097 (0.0099)
NINO3.4 T-3	0.0332** (0.0133)	0.0304** (0.0131)	0.0328** (0.0137)	0.0300** (0.0136)
Decade FE	Yes	Yes	Yes	Yes
Location-Species FE	Yes	Yes	Yes	Yes
Controls	None	Climate	Conflict	Climate + Conflict
<i>Fit statistics</i>				
Observations	704	704	704	704
R ²	0.99566	0.99569	0.99570	0.99572

Driscoll-Kraay (L=4) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S17: Effect of a 1°C Anomaly in the Nino 3.4 Index on Wheat and Rye Grain Harvests.

Dependent Variable:	Log Grain Harvest			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
NINO3.4 T	-0.0435*	-0.0476**	-0.0444*	-0.0462*
	(0.0239)	(0.0239)	(0.0238)	(0.0239)
NINO3.4 T-1	-0.0284	-0.0310	-0.0275	-0.0303
	(0.0227)	(0.0220)	(0.0232)	(0.0224)
NINO3.4 T-2	-0.0268	-0.0294	-0.0274	-0.0292
	(0.0207)	(0.0206)	(0.0204)	(0.0204)
NINO3.4 T-3	-0.0052	-0.0133	-0.0045	-0.0104
	(0.0260)	(0.0258)	(0.0260)	(0.0261)
Decade FE	Yes	Yes	Yes	Yes
Record-Location-Grain FE	Yes	Yes	Yes	Yes
Controls	None	Climate	Conflict	Climate + Conflict
<i>Fit statistics</i>				
Observations	5,349	5,349	5,349	5,349
R ²	0.96388	0.96401	0.96390	0.96400

Driscoll-Kraay (L=4) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

S9.1.3 Non-Linearity Checks

We examine the possibility of nonlinear effects of ENSO by estimating flexible, nonlinear models that allow the impact of ENSO to vary with its amplitude. In particular, we analyzed whether larger El Niño events generate disproportionately stronger effects on all outcomes we study.

We summarize these results in Figure S13 below. Across specifications, we find no evidence of a systematic nonlinear effect: the relationship between ENSO and the outcomes of interest appears to be well approximated by a linear specification, with no clear threshold or amplification at higher ENSO intensities.

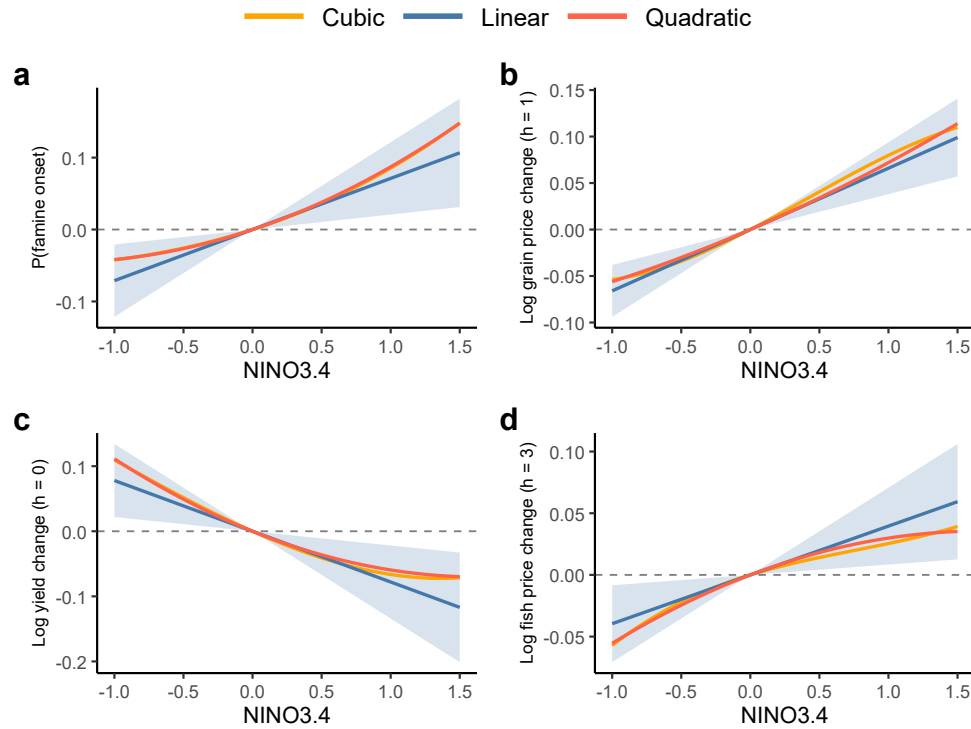
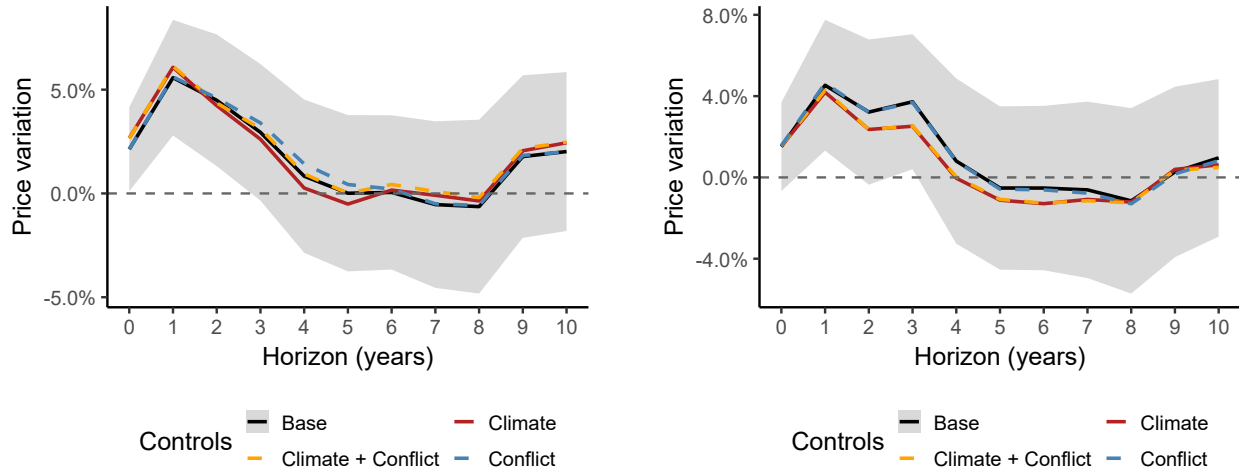


Figure S13: Each panel shows the estimated response to the NINO3.4 index under linear (blue, with 95% confidence interval), quadratic (red), and cubic (orange) functional form specifications. a, Probability of famine onset in Central Europe. b, Grain price variation evaluated at horizon $h = 1$ year. c, Wheat and Rye log yield change in teleconnected regions at horizon $h = 0$. d, Fish price increase at horizon $h = 3$ years.

S9.2 Different Data Sources

Grain Price Data We use alternative grain price datasets, namely Federico et al. [61] and Allen [62], the latter is accessed via the processed version provided by Waldinger [65]. Both grain price compilations have been extensively used in the literature, and both yield extremely close estimates of the ENSO impulse response, in agreement with the one of our main dataset by Ljungqvist and Seim [1].



(a) IRF from a 1°C shock in ENSO on grain prices from the Federico et al. [61] dataset.

(b) IRF from a 1°C shock in ENSO on wheat prices from the Allen [62] dataset.

Figure S14: Impulse response functions (IRFs) of a 1°C shock in ENSO on historical grain prices.

Grain Harvest Data As an alternative measure of harvest outcomes, we use grain yield ratio data from Waldinger [65], based on the compilation by Slicher van Bath [63]. Yield ratio is the ratio of harvested grains to grains used for sowing. A higher yield ratio indicates higher per unit agricultural productivity. While yield ratio data are provided for between 1 and 200 years, the panel is unbalanced. For the majority of locations (346 out of 551), yield data are provided for 1 year only. In some cases, where yield ratios are provided for longer time periods, average yield ratios are provided covering between 2 and 50 years. We include only locations with at least 10 independent observations, following Waldinger [65]. The final yield data sample includes 12 cities in four present-day European countries: France, Germany, Poland, and Sweden.

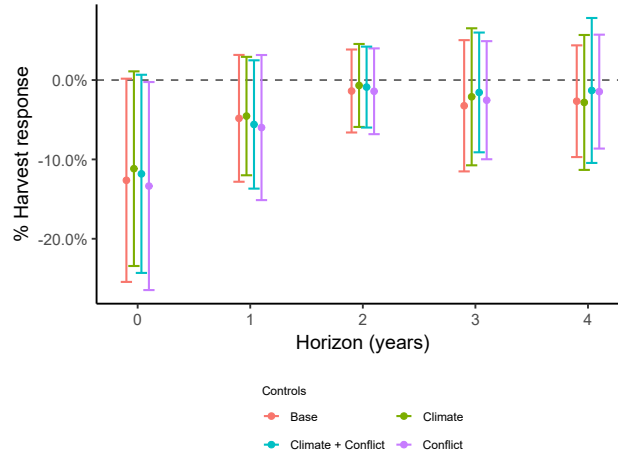
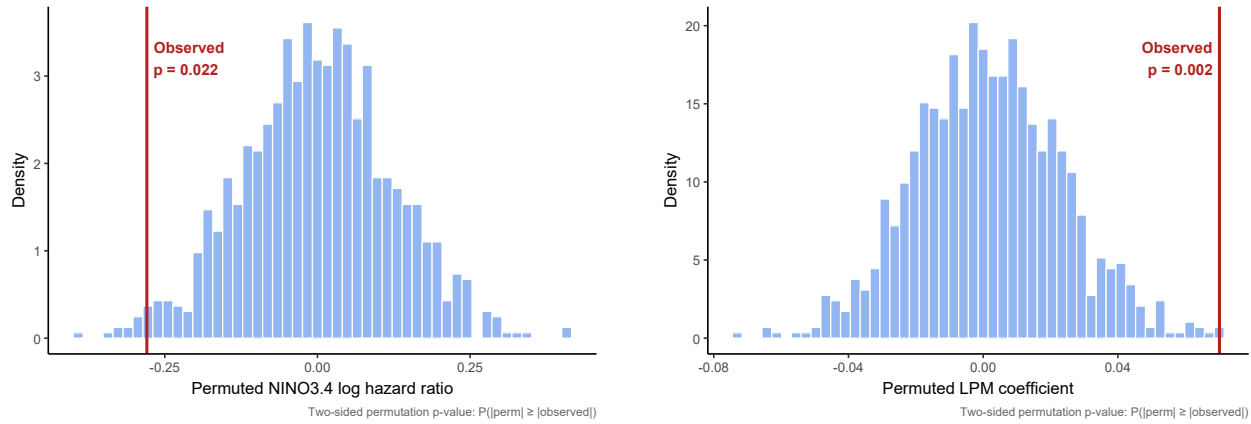


Figure S15: Impulse Response Function of grain yield ratios to a 1 °C anomaly in the NINO3.4 index, using yield ratio data from Slicher van Bath [63].

980 Our estimate of the immediate impact of an ENSO shock on harvests is now even stronger (–15% against –
 981 6.4% in our main harvest dataset), and is robust to different controls (see Figure S15). The stronger response
 982 is presumably due to a larger proportion of data from Central Europe in the smaller dataset by Slicher van
 983 Bath [63] than in our larger main harvest dataset.

S9.3 Permutation Check

We perform a standard permutation placebo test where we shuffle the NINO3.4 index across all samples and report the (null) estimated response functions across bootstraps, following Young and Hsiang [66] and others. We evaluate the robustness of our results using permutation tests for both the Linear Probability Model of famine onset and the Cox proportional hazards model for famine duration. For each model, we compare the baseline coefficient to the distribution of estimates obtained from $N = 10000$ random shuffles. We also perform analogous checks for price and yield local projections ($N = 500$ IRFs), reporting the baseline impulse response function alongside the 95% confidence interval of the placebo simulations. For the famine onset model, the probability of observing the baseline estimate by chance is below 1%, while for the Cox model it is approximately 1% (Figure S16). For the local projection models, we report that our baseline estimates of interest do not intersect with the 95% confidence interval of the placebo simulations (Figure S17), suggesting that the observed effects are statistically robust and unlikely to be driven by random variation.



(a) Distribution of estimated log-hazard ratios of NINO3.4 on famine **hazard**, after random shuffling ($N = 1000$ simulations). The vertical line indicates the true estimate. The reported p -value is the probability of obtaining an estimate below the observed one.

(b) Distribution of estimated coefficients of NINO3.4 on famine **onset** in Central Europe after random shuffling ($N = 1000$ simulations). The vertical line indicates the true estimate. The reported p -value is the probability of obtaining an estimate above the observed one.

Figure S16: Permutation tests for the effect of NINO3.4 on famine dynamics. Panel (a) shows the effect on famine **duration** using a Cox proportional hazards model. Panel (b) shows the effect on famine **onset** in Central Europe using a linear probability model with interaction terms by Region.

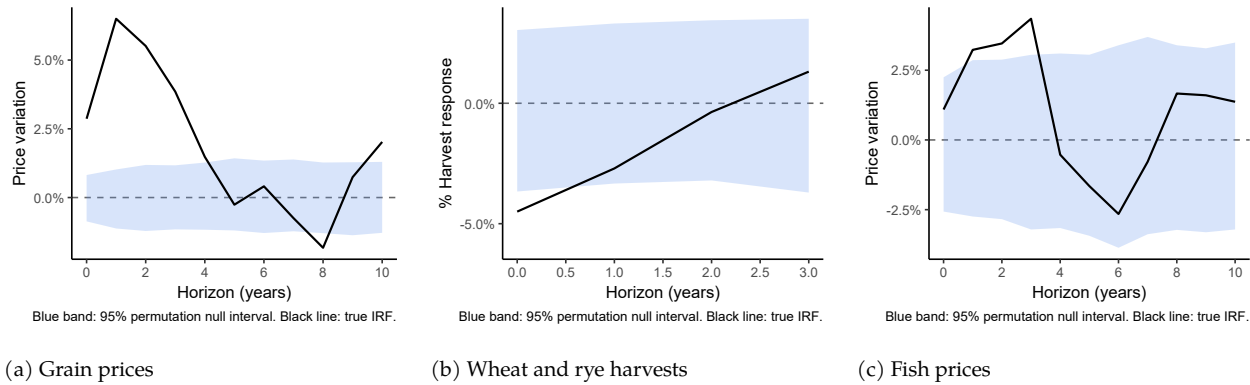


Figure S17: Estimated impulse responses to a 1°C ENSO shock. The black line shows the main specification, with shaded intervals denoting 90% and 95% confidence bands from $N = 500$ placebo shuffle tests.

S9.4 Sensitivity of Famine Onset and Survival models to sample composition

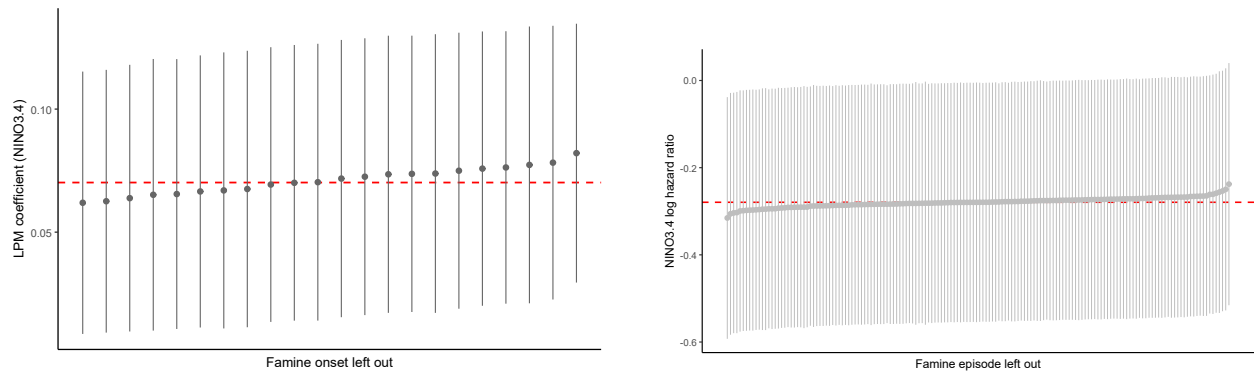
To assess the sensitivity of our ENSO–famine estimates to individual events, we conduct a series of leave-one-out robustness checks. For the famine onset model, we re-estimate the linear probability specification after sequentially excluding each famine start in the Central Europe region, the subset that drives identification of the NINO3.4 interaction. The resulting coefficients remain clustered around the baseline estimate, suggesting that no single onset drives our findings.

For famine duration, we repeat the exercise by excluding one famine episode at a time and re-estimating the Cox proportional hazards model. The estimated log-hazard ratios again remain stable across exclusions, with baseline estimates lying well within the distribution of leave-one-out re-estimates. Taken together, these results demonstrate that our onset and duration findings are not driven by any single famine event, but rather reflect systematic ENSO effects across episodes (Fig. S18).

S9.5 Sensitivity of Impulse Response Functions (IRFs) to sample composition

We show the panel local projection results are robust to estimating on the whole sample, leaving out one location at a time, in Figures S19, S20, S21. In the case of the yield ratio, we see the impact is even more pronounced when we leave out location identifier 327. Location 327 has the highest number of observations so it is indeed influential in the panel, but other panels show a consistent drop in yield as well, in line with the main result.

We then also show the panel local projection results are robust to estimating on the whole sample, leaving out 20-year blocks, on at a time, in order to detect potentially influential time periods, in Figures S22, S23, S24.



(a) Leave-one-famine-out estimates for famine onset (LPM, Central region).

(b) Leave-one-famine-out estimates for famine duration (Cox PH).

Figure S18: Sensitivity of famine-ENSO estimates to individual events. (a) Linear probability model of famine onset with $\text{NINO3.4} \times \text{Central Europe}$ interaction. (b) Cox proportional hazards model of famine duration. Red dashed lines denote the baseline estimates; grey point-ranges indicate the coefficient estimates after dropping one famine at a time.

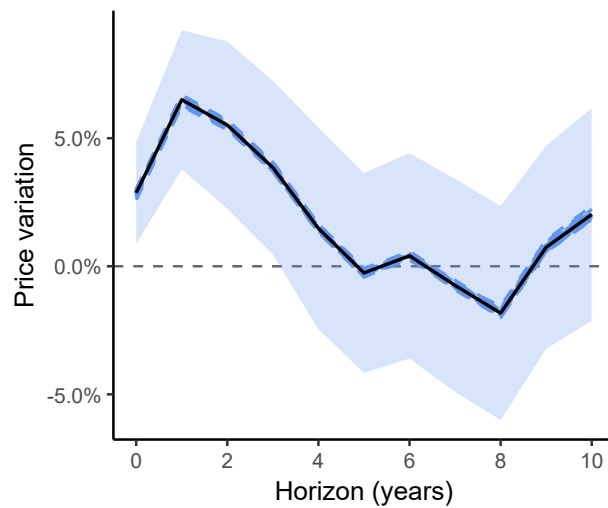


Figure S19: Estimated impulse response functions of grain prices to a 1°C ENSO shock, removing one location at a time.

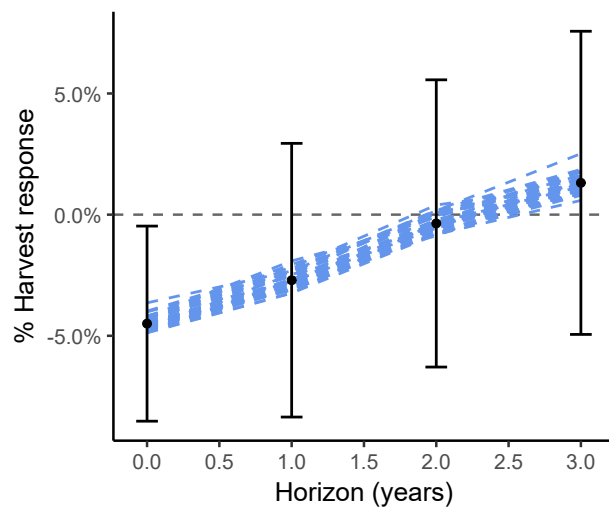


Figure S20: Estimated impulse response functions of grain harvests to a 1 °C ENSO shock, removing one location at a time.

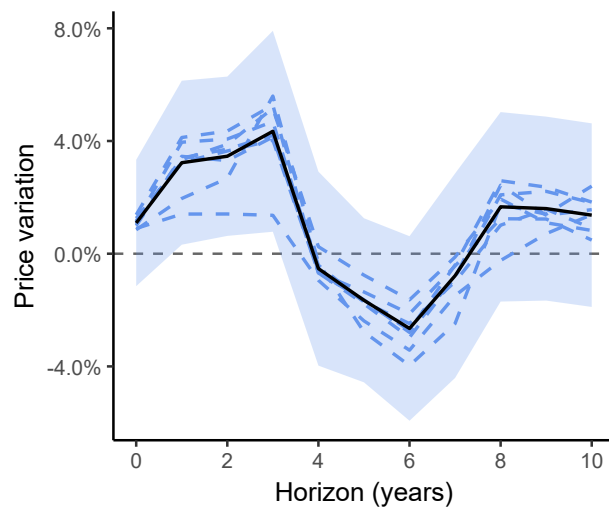


Figure S21: Estimated impulse response Functions of fish prices to a 1 °C ENSO shock, removing one location at a time.

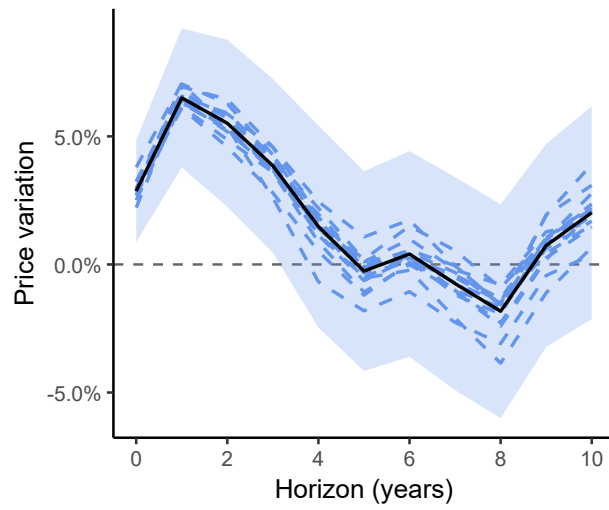


Figure S22: Estimated impulse response functions of grain prices to a 1 °C ENSO shock, removing 20 consecutive years at a time.

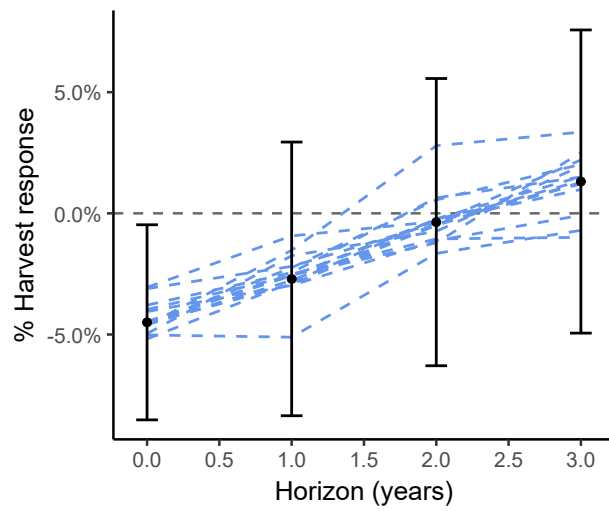


Figure S23: Estimated Impulse Response Functions of grain harvests to a 1 °C ENSO shock, removing 20 consecutive years at a time.

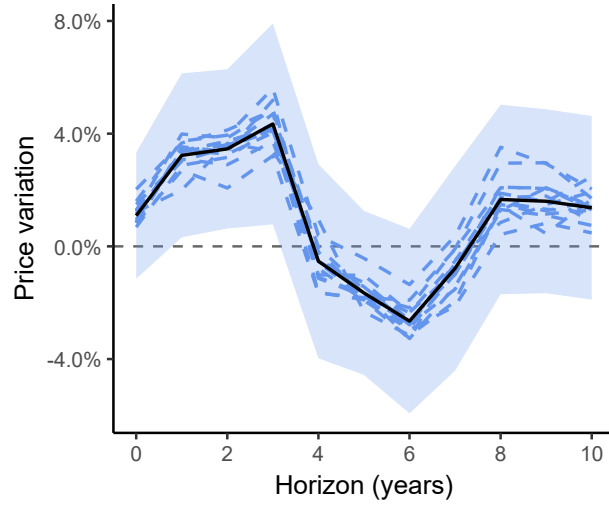
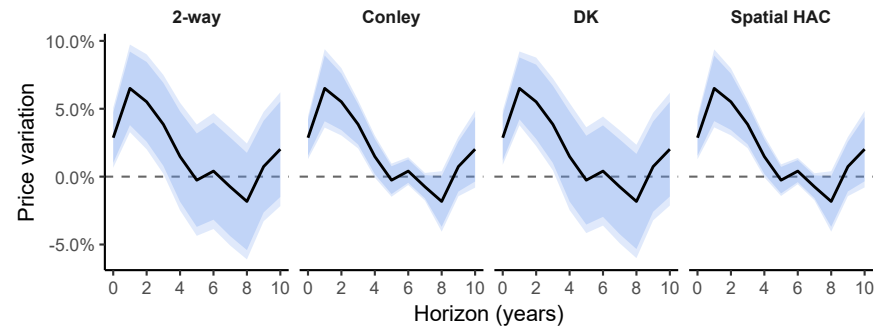


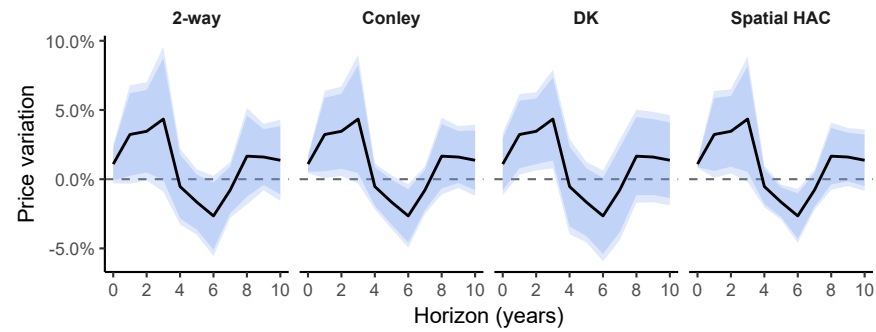
Figure S24: Estimated Impulse Response Functions of fish prices to a 1 °C ENSO shock, removing 20 consecutive years at a time.

S9.6 Robust Standard Errors

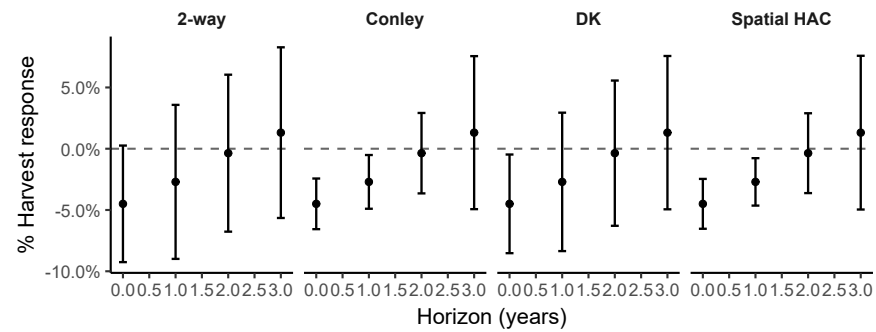
We check that our inference is robust to multiple choices of standard errors in the panel setting. We use Driscoll and Kraay [64] as our baseline, then compare with standard errors assuming both spatial and serial correlation (following Conley [67] and Hsiang [68]) and two-way clustered standard errors at the location and year level. The cutoff for Conley and Spatial HAC is set to 300km.



(a)



(b)



(c)

Figure S25: **Robustness of inference to alternative standard error estimators.** The figure reports impulse response estimates under different assumptions about error structure. Baseline standard errors follow Driscoll and Kraay [64], and are compared with standard errors allowing for spatial and serial correlation [67, 68], as well as two-way clustered standard errors at the location and year level.

Table S18: Granger causality tests for the relationship between ENSO (NINO3.4), prices, and yields.

Variable	Direction	<i>p</i> -value
Grain Price (all cities)	Grain Price → NINO3.4	0.875
Grain Price (all cities)	NINO3.4 → Grain Price	0.001
Harvests (Teleconnected)	Harvest → NINO3.4	0.376
Harvests (Teleconnected)	NINO3.4 → Harvest	0.288
Fish Price (all cities)	Fish Price → NINO3.4	0.995
Fish Price (all cities)	NINO3.4 → Fish Price	0.075

S9.7 Reverse Causality

Although it is highly unlikely, we now alleviate potential concerns about reverse causality of our impulse response estimates. We perform a series of Granger causality tests, summarized in Table S18. We use yearly-averaged time-series for all Granger-causality tests. The results show that NINO3.4 is not forecastable by past values of grain prices or harvests, confirming that reverse causality is not driving our findings. We allow for up to 10 lags when forecasting NINO3.4, and restrict to 1 lag when forecasting our outcome variables (harvests and prices). The lack of statistical significance for harvests likely reflects the fact that the impact of NINO3.4 is largely contemporaneous rather than lagged.

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