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ABSTRACT

A war-related factor model derived from textual analysis of media news reports explains the cross section of expected stock returns. Using a semi-supervised topic model to extract discourse topics from 7,000,000 New York Times stories spanning 160 years, the war factor predicts the cross section of returns across test assets derived from both traditional and machine learning construction techniques, and spanning 138 anomalies. Our findings are consistent with assets that are good hedges for war risk receiving lower risk premia, or with assets that are more positively sensitive to war prospects being more overvalued. The return premium on the war factor is incremental to standard effects.

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An internet appendix is available at http://www.nber.org/data-appendix/w31348

1 Introduction

The catastrophic nature of war has been recognized throughout the ages, from "Vae victis" (woe to the vanquished) in ancient Roman times to Albert Einstein's warning that war threatens to end civilization ("I do not know with what weapons World War III will be fought, but World War IV will be fought with sticks and stones"). In recognition of investor fear of extremely adverse outcomes, financial economists have have developed various measures of tail risk. But the cataclysmic effects of warfare on society suggest that news about war may contain useful information for asset pricing not captured by more generic measures of tail risk.

Rare disaster risk has been proposed as a possible explanation for long-standing asset-pricing puzzles, such as the high equity premium and excess volatility (Rietz 1988, Barro 2006). Time-variation in disaster risk has further been proposed as an explanation for several further puzzles, such as the predictability of equity market returns by price dividend ratios, the cross-sectional predictability of stock returns, and the term spread puzzle (Gabaix 2012, Gourio 2008, and Wachter 2013). The theory that investors fear rare disasters suggests a natural cross-sectional implication: that an asset that provides high returns when a rare disaster occurs is a good hedge and, thus, should have low expected returns (Barro 2006).

A behavioral perspective suggests a similar cross-sectional implication for a different reason: overweighting of the prospect of an extreme disaster. For example, investors may overestimate the probability of disaster because extreme outcomes have high salience (Madan, Ludvig, and Spetch 2014, Hartzmark 2015). Alternatively, investors may overweight low probabilities, as in cumulative prospect theory (Tversky and Kahneman 1992), and extreme disasters are rare. If investors overweight extreme disasters, then investors will overvalue assets whose value is increasing in the probability of disaster. So stocks with higher sensitivity to disaster prospects will earn lower expected returns.

We also test here whether assets with high exposure to disaster risk tend to have lower expected returns. However, our distinctive focus is on war-related disaster risk, which aligns with the themes of Barro (2006) and Hirshleifer, Mai, and Pukthuanthong (2024). Barro (2006) bases disaster probabilities on World War I, the Great Depression, and World War II. Although the Great Depression had profound global economic effects, Barro (2006) argues that in the 20$^{\text{th}}$ century, wars have had greater effects on the world economy than economic contractions. Hirshleifer, Mai, and Pukthuanthong (2024) find that war risk has greater predictive power than other sources of disaster risk, such as economic recessions or pandemics, for aggregate stock and bond market returns. We study here whether the war risk measure of Hirshleifer, Mai, and Pukthuanthong (2024) can be extended to develop predictors of cross-sectional variation in expected returns.

A key challenge to testing the effects of disaster risk on asset pricing is that measures of such risk are noisy, since major disasters are rare. On average, a country experiences an international political crisis once every 15 years, a full-scale war once every 74 years, and an internal conflict once every 119 years (Berkman, Jacobsen, and Lee 2011). We address this issue by focusing on monthly variations in investor attention to war risk as reflected in news media, instead of on realized war events. Textual news material contains information about current expectations of market performance, and other financial and macroeconomic variables (Gentzkow and Shapiro 2010; Mullainathan and Shleifer 2005). Since media attention to war risk shifts continually, there is a large sample of variation in our measure of war risk perceptions. Our approach, therefore, circumvents the issue of a limited sample size inherent in the use of realized rare disasters.

To do so, we build on the measure of Hirshleifer, Mai, and Pukthuanthong (2024), who construct a monthly proxy for attention to war risk (hereafter, *War*) from *The New York Times* (*NYT*) since 1871. They apply a semisupervised topic modeling method called Seeded Latent Dirichlet Allocation (sLDA) developed by Lu et al. (2011) to extract topics from news. The sLDA method allows them to perform a rolling estimation using only past information to forecast future returns. This method avoid look-ahead bias, a core issue for testing asset return predictability.[1] In addition, the technique allows the discourse topics to adjust for

[1] Traditional LDA is subject to a dilemma—either use the entire sample to estimate the model, in which case there is look-ahead bias, or use a rolling forward estimation approach, in which case each month the set of extracted topics changes. Under that rolling forward approach, topics become hard to interpret, and it is not feasible to describe how attention is shifting between given topics, since the nature of the extracted topics can shift arbitrarily over time. Specifically, under traditional unsupervised LDA, the model arbitrarily gathers words into topics based on word co-occurrences. In contrast, under the semisupervised model or sLDA, the use of seed words for each topic constrains the content of topics to be extracted. sLDA fits our research goal of testing the consequences of disaster-focused and non-disaster-focused themes in media discussions. In this approach, we feed the model with the seed words associated with each topic and let the algorithm choose the phrases that often appear with these seed words. The outcome of sLDA depends upon the choice of seed words, so seed words must be chosen based upon economic importance and stability of meaning. The use of seeding constrains the estimation, which has the further possible advantage of reducing overfitting. We use the rolling estimation using the information over the past ten years to compute the topic

semantic changes over time.

We modify the war index of Hirshleifer, Mai, and Pukthuanthong (2024) by using a parsimonious approach of using one seed word, "war." This approach allows us to address the possible concern of multiple testing when there is researcher discretion in seed word choices.[2] We construct a war factor (hereafter, WarFac) as a shock to the news-based *War* index. To avoid look-ahead bias, we use rolling estimation, and define WarFac as the residual from an AR(1) process fitted to the War index.[3]

There has been considerable discussion in the literature of the "Factor Zoo," in which many different factors and factor models have been proposed to explain the cross section of expected asset returns. We provide an especially parsimonious model, in that, like the CAPM, our factor model consists of just a single factor—either the WarFac or the WarFac factor-mimicking portfolios (henceforth, WMP). We present the result of the WarFac first and provide a robustness check using WMP.

In brief summary, WarFac generates significant and negative return premia across six test assets. In cross-sectional tests of factor models, inferences typically depend heavily on the set of test assets (Giglio, Xiu, and Zhang 2021 and Stambaugh 1982). Furthermore, a low dimensionality of the space of test assets tends to favor the conclusion that factors constructed by corresponding characteristics provide a good fit (Daniel and Titman 1997, Lewellen, Nagel, and Shanken 2010). To address these concerns, we employ a large set of test assets that span various dimensions of characteristics based on both direct sorting and machine learning construction, both obtained from public sources and constructed by us:

1. 138 long-short portfolios from Hou, Xue, and Zhang (2020) (hereafter, HXZ),
2. 1,372 single-sorted portfolios from HXZ,
3. 904 single-sorted portfolios from Chen and Zimmermann (2022) (hereafter, CZ),
4. 360 machine learning-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023),
5. Our own constructed 128 long-short portfolios that we constructed based on the same

weight in each month.

[2]We thank the editor for this suggestion. Our results are robust to the use of the original five seed words from Hirshleifer, Mai, and Pukthuanthong (2024). We also present robustness results for the use of various seed words and numbers of topics in E.3.

[3]Along with this, we also make use of the residual from rolling estimation of the ARMA(1,1) process as WarFac. The return premium of WarFac remains significant for both methods. (The results from ARMA(1,1) are a bit weaker, but of comparable statistical and economic significance.)

characteristics used by Hou, Xue, and Zhang (2020),

6. Our own constructed 2,190 nonlinear portfolios sorted by one to three polynomials with similar characteristics as those used by Hou, Xue, and Zhang (2020).

The fifth set of assets captures additional anomalies and the sixth set captures the non-linear characteristics of the portfolios. For the fifth set of test assets, we replicate the anomaly construction approach implemented by Hou, Xue, and Zhang (2020). The sixth set of test assets explores non-linear functions of characteristics using polynomial sorts, complementing the machine learning approach of Bryzgalova, Pelger, and Zhu (2023).[4]

We apply the standard two-pass asset pricing test (Cochrane 2005, Chapter 12) to examine whether a factor is useful for predicting the cross section of asset returns. This consists of two steps. First, factor loadings are estimated to verify whether the factor helps explain contemporaneous returns for a broad set of test assets. The second step tests whether factor loadings help explain the cross section of expected returns. In a rational setting, this would reflect the effects of risk premia associated with the factor.

For the first step as applied to WarFac, we present the number of significant loadings of WarFac in comparison with ten other nontraded factors. We compare to nontraded factors since traded factors, as stock returns, mechanically have a greater propensity to generate significant loadings.

We find that among all nontraded factors considered, WarFac has the highest number of significant loadings for 138 long-short portfolios from HXZ and our own anomaly portfolios. This suggests WarFac has broad explanatory power across many portfolios. However, the high number of betas alone does not necessarily imply WarFac commands a return premium. That determination depends on the second stage results. We find the return premium on WarFac is negative and significant for *all* test assets. In terms of economic magnitude, the return premium of WarFac always rank in the top three out of the 11 nontraded factors across all test assets.[5] No other traded factor shows such a consistency in both statistical

[4]As mentioned above, our fourth set of assets are based on tree-based portfolios from Bryzgalova, Pelger, and Zhu (2023). These portfolios capture complex nonlinear relationships and interactions. We thank Professor Markus Pelger for providing the data. Our sixth set of assets follows the methodology of Kirby (2020) in using first to third degree polynomials to model nonlinear effects of characteristics. The polynomial approach is transparent and simple; tree-based models are more flexible in capturing nonlinear effects. See Appendix H.2 for a description of how the fifth and sixth sets of test assets are constructed.

[5]We rescale other nontraded factors to have the same standard deviation as WarFac so that coefficients are comparable for evaluating their economic significance.

and economic significance across the test assets. For example, several nontraded factors, such as the news-based consumption risk factor and macroeconomic principal components, have many test assets with significant loadings, but these loadings do not command significant risk return premia.

For the second step, we compare the return premium of WarFac as a single-factor model to other leading factor models including the Fama-French six-factor model (FF6), the Stambaugh and Yuan (2017) mispricing factor model (M4), the Daniel, Hirshleifer, and Sun (2020) composite behavioral and rational factor model (DHS), and the Hou et al. (2021) q-factor model (Q5). Unlike the first step above, here we compare the return premium of WarFac with the premia of traded factors. (The results for WMP, as defined above, are similar and reported in Internet Appendix C.)

We find that WarFac exhibits a substantial and statistically significant return premium which remains stable when applied to the cross sections of various sets of test assets. Notably, WarFac excels in pricing returns of the machine learning-based nonlinear portfolios of Bryzgalova, Pelger, and Zhu (2023) (hereafter, ML-based nonlinear portfolios). Using these ML-based nonlinear portfolios as test assets, WarFac as a stand-alone factor model outperforms various well-known factor models, explaining 62% of the variance in the test assets.

Furthermore, WarFac as part of a factor model consistently generates low and statistically insignificant common pricing error (the intercept) for these ML-based nonlinear portfolios—much lower than the errors generated by other benchmarks. For example, the intercept is 1.2% for WarFac as a solo factor model versus 3.3% as the average of intercepts from the four alternative asset pricing factor model benchmarks that we consider. Even the lowest such intercept is 2.11%, which is considerably higher than the intercept for WarFac as a solo factor model. When we incorporate WarFac into multi-factor benchmarks, the common cross-sectional pricing error dramatically shrinks from 3.3% to 0.5%.

Furthermore, when pricing ML-based nonlinear portfolios, WarFac has the most significant cross-sectional sensitivity of mean returns to loadings (in rational settings, the market price of risk; more generally, the return premium slope). Also, this sensitivity for WarFac is approximately two to four times higher for the ML-based portfolios in magnitude than for other sets of test assets.[6]

[6]When pricing ML-based nonlinear portfolios, WarFac's return premium slope stands at -3.3%, compared

Bryzgalova, Pelger, and Zhu (2023) find that ML-based nonlinear portfolios capture interactions among many characteristics in their effects on returns. They argue that their test assets are more challenging to price than conventional assets such as portfolios sorted on size and book-to-market. Uniquely among factor models, as far as we know, WarFac prices these assets very well. These results provide support for the theories that disaster risk commands a negative risk premium or that, for behavioral reasons, more disaster sensitive stocks are more overpriced.

Turning to the traded version of the war factor, WMP also consistently has a negative and significant beta return premium. The traded version allows multiple tests in addition to the two-pass test. Under the spanning test, WMP generates significant alphas against benchmark factor models, suggesting that it contains incremental pricing information and can be combined with factor models to better span the return space. Our results are consistent with various methods of mimicking-portfolio construction, including cross-sectional and time-series approaches. Within the time-series approach, the result is consistent across different basis assets. The basis assets are the excess returns of assets onto which we project the non-traded factors. In principle, the basis assets should summarize much of the return space.

WMP also satisfies the conditions of the protocol for factor identification of Pukthuanthong, Roll, and Subrahmanyam (2019) and passes the three-pass test proposed by Giglio and Xiu (2021), consistent with WarFac being a priced risk factor.

We perform a battery of sensitivity analyses to evaluate the robustness of our findings with respect to alternative ways of constructing the war factor. We construct the *War* index using different variants of seed words, including the five seed words used by Hirshleifer, Mai, and Pukthuanthong (2024); the seed words without "terrorism,"[7] the new seed words for *Pandemic*; and including more topics. Although the results of using sLDA depend on the choice of seed words and topic number, the modified WarFac, constructed from the variants of seed words and topic numbers, remains strong and generates robust results.

Unsupervised LDA differs in identifying seed words and topic number without human intervention. As a comparison, we construct a war factor using the topics chosen by unsu-

to -1.3% for HXZ's long-short portfolios, -0.7% for HXZ's single-sorted portfolios, and -1.3% for CZ's single-sorted portfolios.

[7]Terrorism could be connected to war risk, especially since the 9/11 attacks.

pervised LDA in Bybee et al. (2024). We compute an average of the war-related topics, fit an AR(1) to this average, and take the residuals as a war factor.[8] We find that the war factor generated from the war-related topics using unsupervised LDA is not associated with a return premium whereas WarFac is.

We next perform several tests to provide economic insight into WarFac. First, we show that the war risk captured by WarFac is distinct from the other betas that capture downside risk including CAPM beta, bear beta (Lu and Murray 2019), downside beta (Ang, Chen, and Xing 2006), relative downside beta (Ang, Chen, and Xing 2006), VIX beta (Ang et al. 2006), volatility beta (Cremers, Halling, and Weinbaum 2015), jump beta (Cremers, Halling, and Weinbaum 2015), co skewness (Harvey and Siddique 2000), skewness beta (Chang, Christoffersen, and Jacobs 2013), tail beta (Kelly and Jiang 2014), and idiosyncratic volatility (Ang et al. 2006). When we control for the mimicking portfolios of these betas, WarFac remains significant, suggesting that WarFac captures a war risk distinct from the other kinds of downside risks that investors are concerned with.

Our paper hence addresses a key economic issue: what *kinds* of tail risks are priced in the cross section? Is the pricing of tail risk primarily about the probability of extreme returns, regardless of the underlying source? Is pricing instead associated primarily with concern about economic events such as extreme recession? Or, is a concern with a different specific source of tail risk, war, incrementally important? Our research indicates that war is a key risk for asset pricing, and that the effects of measures of market attention to war are not captured by existing proxies for downside risk in the finance literature.

Second, articles can take the form of pure news pieces or opinion pieces. We answer whether analytical news contributes to the significant return premium of WarFac. The interpretation of the results from the news is more straightforward than that of the analytical piece. We identify the months in which WarFac generates the most significant return premium and examine whether analytical pieces drive the results. During those months, we find no evidence for the association between war-related and analytical coverage, suggesting that analytical news is not the driver of our results.

Third, we investigate possible asymmetry in the pricing capability of WarFac by parti-

[8] As mentioned, under LDA, there is no one topic specifically for War. We thus use the average of the scores for the war-related topics, which we identify as [US_defense, Russia, Nuclear_North_Korea, Iraq, Terrorism, National_security]. We thank the authors for publicly providing their data on a companion website.

tioning WarFac into a positive component, WarFac$^+$ (an upward movement in *War* index, assigned a value of zero when WarFac is negative), and a negative component, WarFac$^-$ (a downward movement in *War*, assigned a value of zero when WarFac is positive). We find that both WarFac$^+$ and WarFac$^-$ substantially contribute to the return premium of WarFac. Furthermore, after controlling for other topics, the return premium associated with WarFac$^-$ persists, suggesting that downward movements of *War* (less market attention to *War*) are not just a reflection of market distraction by other topics.

Within the literature on disaster risks and news, Manela and Moreira (2017) (henceforth, MM) apply a machine learning approach to construct a news-based measure of uncertainty from the front page of *Wall Street Journal (WSJ)* from 1890, called NVIX, and Caldara and Iacoviello (2022) construct a geopolitical risk index from news using dictionary approach. After controlling for their measures, WarFac provides incremental predictive power, resulting in a negative and significant return premium. In contrast, these two media-based uncertainty measures do not yield significant return premia. Hirshleifer, Mai, and Pukthuanthong (2024) further discuss the differences between these measures in predicting aggregate market returns.

Bybee et al. (2024) use traditional unsupervised LDA on news content to fit contemporaneous financial and macroeconomic variables and to forecast both macroeconomic variables and the aggregate stock market return. Bybee, Kelly, and Su (2023) construct asset pricing factors from news media text and find that their news factors price 78 anomaly portfolios and 25 portfolios sorted on size and book-market.

Our paper differs from Bybee, Kelly, and Su (2023) in three main ways. First, Bybee, Kelly, and Su (2023) develop a set of six traded factors from 180 news topics, whereas we construct one factor from the *War* topic to test the effects of rare disaster risk. It is interesting to test how well a very parsimonious model that uses only a single factor can price the cross section of expected returns. Second, as test assets and benchmarks, Bybee, Kelly, and Su (2023) use 78 anomaly portfolios and 25 portfolios sorted on size and book-market and benchmark pricing performance against the Fama-French six-factor model (Fama and French 2018). In contrast, we use six sets of test assets covering hundreds of characteristics and benchmark our single-factor model against four prominent factor models. Third, Bybee, Kelly, and Su (2023) use an unsupervised topic model to extract topics from economic news in the *WSJ* from 1984 to 2017, while we apply a semisupervised topic model to extract war risk from all news in the *NYT* from 1871 to 2019. We use the *War* index from 1926 to

2019 in asset pricing tests as data on portfolio returns is available starting in 1926. The key advantages of our semisupervised approach are that it accounts for semantic shifts over time, and that *War* is available in real-time, so that our tests are not subject to look-ahead bias. Our study is the first to examine whether an empirical measure of rare disaster risks captured by *War* receives a return premium over a broad cross section of assets.

An existing literature studies whether downside tail risk or time varying volatility helps predict the cross section of expected returns. Our study differs in the following ways.

First, some studies focus on volatility rather than disaster risk. In contrast with the volatility beta investigated by Chang, Christoffersen, and Jacobs (2013) and Cremers, Halling, and Weinbaum (2015), our war risk measure focuses on potential left-tail outcomes.

Second, several studies test for the effects of asymmetries between upside and downside risk. Harvey and Siddique (2000) find that assets that make the portfolio returns more left-skewed have higher expected returns. Ang, Chen, and Xing (2006) provide evidence suggesting that downside risk is priced more heavily than upside risk.

Our approach differs in focusing on changes in the perceived probabilities of future downside market states rather than the realized downside market states used to calculate their downside beta. Our research is more closely related to the literature on tail risk and jump risk estimation for explaining the cross section of expected returns. Kelly and Jiang (2014) use realized returns for tail risk estimation. In contrast, we adopt an approach using news data.

A series of studies, including Santa-Clara and Yan (2010), Bollerslev and Todorov (2011), Christoffersen, Jacobs, and Ornthanalai (2012), Andersen, Fusari, and Todorov (2015), Cremers, Halling, and Weinbaum (2015), and Lu and Murray (2019) apply options data to measure jump risk. These approaches are powerful but subject to data limitations. The options data are more reflective of jumps or movements that occur at a high frequency. The data capture few of the very rare but most devastating events. The options data are available for less than 30 years, while our study uses a much longer sample period (nearly 100 years for the test of industry portfolios and 45 years for the test of anomaly portfolios). As emphasized by Lundblad (2007), since stock returns are highly volatile, it is crucial to consider long-time series data to test for return predictability reliably.

Lastly, Gourio (2008) develops a theory to explain the ability of disaster risk to explain the cross section of expected returns. Empirically, he does not find a significant return premium, which he attributes to having a poor estimator of disaster risk. Berkman, Jacobsen, and Lee (2011) use crisis event counts to test whether disaster risk prices the Fama-French 30 industry portfolios. They benchmark against the Fama-French three factors.[9] In contrast, we consider a much more extensive set of test assets and benchmark our pricing results against more recent leading factor models such as the Fama-French six-factor model (FF6), the Stambaugh and Yuan (2017) mispricing factor model (M4), the Daniel, Hirshleifer, and Sun (2020) composite behavioral and rational factor model (DHS), and the Hou et al. (2021) q-factor model (Q5).

2 Method and Data

We use the sLDA model (Lu et al. 2011) to extract specific news discourse topics. We follow the setup in Hirshleifer, Mai, and Pukthuanthong (2024), who study the ability of 2 disaster- and 12 non-disaster-focused topics to predict aggregate market returns and find strong performance of *War*. In this paper we use of *War* to develop predictors of the cross section of stock returns.

In this section, we briefly discuss the setup and implementation of their method and the news data used to extract the topics. A more extended intuitive description is provided in Hirshleifer, Mai, and Pukthuanthong (2024); we provide a detailed description in Internet Appendix A.1.

2.1 Stochastic Topic Models

In topic models, each document is modeled as being generated in a three-step stochastic process (Blei 2012; Steyvers and Griffiths 2007). In the first step, a vector is randomly selected for each document that indicates the probabilities of different topics in the document. This is called the *document-topic distribution*. Next, for each word position in the document, we randomly pick a topic from this document-topic distribution. Finally, at this position, we

[9]We find that WarFac provides pricing power incremental the crisis and war count factors of Berkman, Jacobsen, and Lee (2011) as detailed in Subsection 5.2. In unreported results, we find that the crisis and war count factors from Berkman, Jacobsen, and Lee (2011) yield significant positive return premia when pricing the six sets of test assets discussed above, inconsistent with the rational rare disaster asset pricing models which predict negative return premia.

randomly select a word from the distribution of words for the selected topic. This process is repeated for all word positions in the document.

For each topic, the vector of probabilities of different words is global and is called the *topic-word distribution*. The document-topic and topic-word distributions are characterized by latent parameters we need to estimate. We use statistical methods to infer the topic weights underlying each document from word frequencies in a collection of documents.

The most widely used topic model is latent Dirichlet allocation (LDA) introduced by Blei, Ng, and Jordan (2003) and further developed by Griffiths and Steyvers (2004). Under LDA, the document-topic distribution (again, a vector of probabilities over the topics) for a given document and topic-word distribution (again, a vector of probabilities over the words) for a given topic each is randomly selected from a prior Dirichlet distribution characterized by a pre-specified hyperparameter. Under this hierarchical setup, we can use a Bayesian estimation technique called Gibbs sampling to infer the document-topic and topic-word distributions for each document and topic.

Estimating the document-topic distribution is of interest because it gives us the proportion of document content related to each topic. Aggregated over documents, this gives an estimate at any given time of how heavily media discourse is focused on different topics.

Under the traditional unsupervised LDA model, the researcher must pre-specify the number of topics, and the model is free to cluster words into topics. In contrast, in this paper, we follow Hirshleifer, Mai, and Pukthuanthong (2024) in studying specified topics of economic interest. We therefore apply a recent extension to the LDA model called seeded latent Dirichlet allocation (sLDA), which allows users to give domain knowledge in the form of seed words to guide the clustering of words into predefined topics.

In addition to giving users control over topic content, sLDA produces consistent thematic content across different estimations, another advantage over the unsupervised LDA model. This feature is crucial as it facilitates rolling estimations of the model to avoid look-ahead bias and account for language changes over time. As discussed in Subsection 2.3 below, every month t, we use the rolling 10 years (including month t) of news data to estimate the sLDA model. This estimation scheme allows us to use only available data to estimate topic weights, avoiding the look-ahead bias of using future news data in estimating current topic weights. Moreover, under rolling estimations, words clustered into topics change monthly based on their usage at each estimation date, allowing for language changes over time. See

Internet Appendix A.1 for more details about LDA and sLDA.

2.2 Seed Words

A key component of an sLDA model is the set of seed words representing the prior knowledge of each topic. As emphasized by Watanabe and Zhou (2020), a dictionary of seed words must be carefully chosen based on field-specific knowledge independent of word frequencies in the text collection. In contrast to Hirshleifer, Mai, and Pukthuanthong (2024) whose *War* relies on five seed words including *conflict, tension, terrorism, terrorist, and war*, for parsimony we rely here on only one seed word, *war*.[10] In addition to *War*, Hirshleifer, Mai, and Pukthuanthong (2024) also study *Pandemic* and 12 economic topics drawn with slight modifications from Shiller (2019) and include one additional "garbage collector" to absorb everything else in the news unrelated to these topics.[11] See Table A.1 for each topic's list of lemmatized seed words. ("Lemmatization" removes word endings such as *s, es, ing, ed.*)

Barro (2006) also uses information about war to estimate the parameters of his model. He finds that war risk explains the equity premium puzzle. As mentioned in the introduction, *War* outperforms the other topics in predicting stocks returns both in- and out-of-sample. Based on this past evidence, we focus on *War* in this paper.

2.3 Estimation

Figure 1 illustrates the rolling estimation scheme used in the paper. At the end of each month t, we run the sLDA model using all news data over the past 120 months (months $t-119$ to t). We use ten years of news data in the monthly estimation to balance the amount of news data required to estimate the model and computational costs. On average, every ten years of historical data consists of around 460,000 articles, sufficient to reliably extract the topic weights at the time of estimation.

During each monthly estimation, we use Gibbs sampling to estimate the vector of topic weights for each document in month t. We compute the global monthly weights of each topic

[10] Our results remain robust to using the original five seed words for *War* (see Subsection 7.3).

[11] The other topics include *Panic, Confidence, Frugality, Conspicuous Consumption, Monetary Standard, Technology Replacing Jobs, Real Estate Boom, Real Estate Crashes, Stock Market Bubbles, Stock Market Crashes, Boycotts, Evil Business,* and *Wage and Labor Unions.*

as the average weight of each topic across all articles in month t, weighted by the length of each article. See Internet Appendix A.2 for more details of the estimation.

While the final topic weights in month t are computed from the news articles of that month only, we use ten years of news articles to estimate the model each month. The final output of the estimation process is a time series of monthly weights for each of the 14 topics. The topic of interest in this paper is *War*, whose time series is used to construct the *War* factor used in our asset pricing tests.

2.4 News Data

We exploit the richness of full newspaper texts using articles since the beginning of the *NYT*'s inception. We remove articles with limited relevant content, such as those that contain mostly numbers, names, or lists. We then perform the standard text processing steps (following the text cleaning procedure described in Internet Appendix A of Hirshleifer, Mai, and Pukthuanthong (2024)).

After the cleaning steps, for each month t we create a document term matrix containing all articles over the past ten years up to the current month. Each row of the matrix is an article, each column is a term, and each entry is the count of that term in the article. The document-term matrix and topic-based seed words are input into the sLDA model to estimate monthly topic weights, as described in the preceding section.

Since 1871, the *NYT* has published over 6.8 million news articles with an average monthly of 3,800. (Data are missing for September and October 1978 due to strikes.) Over 1871–2019, articles come in at an average length of 493 $n$grams, including unigrams (one-word term), bigrams (two-word terms), and trigrams (three-word terms). Figure A.1 plots our sample's monthly counts and average length of *NYT* articles.

3 Textual Discourse about War Risk

We next describe the *War* index constructed by sLDA. We first discuss the words clustered into the *War* topic by sLDA and its evolution over more than 100 years.

During each monthly estimation, we keep the 30 words with the highest probabilities in the *War* topic as the output of the sLDA model. In Figure 2, we plot the word cloud of these *War* words: the higher the frequency of a word over time, the bigger its size in the plot. The words clustered into the *War* topic are consistent with the initial seed words. The most important words for *War* over time are *conflict, war, government, state, tension*, and *military*.

War captures investor attention to war and war-related events. We can interpret the index as the fraction of an article's text devoted to the topic *War*. The mean of monthly *War* (i.e., average of article-level *War* weighted by each article's length) is 9.71%, suggesting that about 10% of the monthly *NYT* coverage is about war-related news.

Panel A of Figure 3 shows that *War* spiked in the 1870s during the Reconstruction period following the American Civil War and surged again during the 1890s, marked by the Spanish-American War and Philippine-American War. *War* reached its highest level since the start of the sample during World War I and remained low during the 1920s and 1930s before surging again during World War II.

In Panel B of Figure 3, we zoom in on the last 30 years of the sample and identify the ten articles with the most significant contributions to the ten highest monthly scores of *War* hikes since 1990. Panel B of Figure 3 shows that *War* spiked during the Gulf War in the early 1990s and again after the 9/11 terrorist attacks in 2001. In recent years, War has remained high, particularly from 2014 to 2018, reflecting the period of international tensions, including the nuclear weapons development and tests by North Korea.

4 *War* Discourse and the Cross Section of Expected Returns

In the next subsection, we discuss the theoretical background. Then, in Subsection 4.2, we present the asset pricing framework. The last three subsections discuss test assets and results.

4.1 Theoretical Background

Hirshleifer, Mai, and Pukthuanthong (2024) provide evidence that *War* positively predicts the aggregate stock market return. This paper tests whether a factor based on *War* can be used to predict the cross section of expected stock returns. In particular, we test whether loadings on this factor are negative return predictors.

Such a relationship is implied by rational models of rare disaster risks (Barro 2006, 2009) as discussed in Gourio (2008). In such a setting, investors require a risk premium for bearing greater war risk (beyond the standard CAPM premium for beta), perhaps because of a stochastically varying investment opportunity set (Merton 1973). Stocks that provide high returns during periods of high *War* risk provide a hedge for aggregate consumption and therefore command low return premia.

Such a relationship is also a consequence of a behavioral perspective in which investors overweight war prospects. This implication builds on models in which imperfect rationality affects the cross section of expected returns. In the model of Daniel, Hirshleifer, and Subrahmanyam (2001) when there are imperfectly rational investors as well as rational arbitrageurs, in equilibrium mispricing generates cross-sectional return predictability, and behavioral factors are priced. As pointed out by Kozak, Nagel, and Santosh (2018), the covariance structure and expected returns of individual assets are linked, which places bounds upon the Sharpe ratios of behavioral factors. This leads to deviations from the cross sectional asset pricing model that would apply under perfect rationality (see, e.g., Daniel, Hirshleifer, and Sun (2020)).

Specifically, major disasters are highly salient, and the psychology of attention suggests that people overestimate the probabilities of salient events. Also, under cumulative prospect theory preferences, investors overweight low probabilities. This implies that rare risks (including the risk of war) are overweighted. In either case, investors overvalue assets that will do well in the event of war, as investors place a high value on the fact that such assets are good hedges. Such stocks will subsequently tend to earn low returns. In contrast, stocks that are negatively sensitive to war prospects (i.e., will do poorly in the event of war) will be undervalued and tend to earn high returns. So expected returns across stocks tend to decrease with the loadings on the *War* factor. Higher loadings mean that a stock is less negatively (or more positively) sensitive to the war risk that investors are pessimistic about. In other words, factor loadings proxy for mispricing.

Gourio (2008) derives a framework for testing the cross-sectional implications of rare disaster premia. He defines rare disasters as the states of the economy when the monthly market returns are below 10%, or the annual consumption growth is lower than -2.3%. Gourio

(2008) does not find empirical support for the cross-sectional version of the rare disaster risk model. However, extant measures of variation in rare disaster risk that are based on ex-post realizations, such as that used in Gourio (2008), have small sample sizes. This limits the power to identify effects.[12]

We use news data to capture investors' perceptions of disaster risk, as extracted in our *War* index. We test for the ability of our *War* factor in a linear factor model to price characteristic-sorted portfolios from July 1972 to December 2016 and industry portfolios from 1926 to 2018 in Subsection 5.2.[13]

4.2 Asset Pricing Framework

To estimate factor loadings β_{if} and the return premium λ_f, we perform the standard two-pass test (Cochrane 2005, Chapter 12). First, for each asset $i = 1, \ldots, N$, we estimate the factor loadings from the time-series regression:

$$R^e_{it} = \alpha_i + \beta'_{iF} F_t + \epsilon_{it}, \quad \text{for } i = 1, \ldots, N \tag{1}$$

where R^e_{it} is the excess return of asset i at time t and F_t presents a vector of factors. Then, to estimate the return premium slope associated with factors F_t, we perform a cross-sectional regression of time-series average excess returns, $\overline{R^e_{it}}$, on factor exposures:

$$\overline{R^e_{it}} = \lambda_0 + \beta'_{iF} \lambda_F + e_i. \tag{2}$$

This regression gives estimates of the cross-sectional return premium slope λ and the common cross-sectional pricing error (intercept) λ_0. Under rational factor pricing, the intercept (λ_0) is predicted to be zero. Under either the rational factor pricing or behavioral pricing theories, the return premium slope (λ_f) is predicted to be substantial and stable across different cross sections of test assets.

[12]Gourio (2008) uses the returns during 9/11, natural disasters, and low consumption. He argues that if there are large risk premia for rare disasters, industries that did well on 9/11 (e.g., defense, tobacco, gold, shipping and railroad, coal) should have low return premia. On average, industries that did poorly (e.g., transportation, aerospace, cars, leisure) should have high return premia.

[13]We start our sample period for characteristic-sorted portfolios in July 1972 since it is when the DHS factors are available. The sample ends in December 2016 because the mispricing factors of Stambaugh and Yuan (2017) and the ML-based portfolios of Bryzgalova, Pelger, and Zhu (2023) are available through 2016. The pricing results for our *War* factor are robust for the sets of portfolios available until October 2019, the end of our *War* index.

In our estimates, we report the t-statistics computed with the corrected standard errors of Shanken (1992). The variable e_i captures the pricing error, predicted to be zero under rational factor pricing. To measure the size of pricing errors, we report the cross-sectional $R^2 (= 1 - \sigma_e^2/\sigma_{\mu_R}^2)$ and mean absolute pricing error MAPE $(= \bar{|e|})$. Under rational factor pricing, the R^2 should be 1, and MAPE should be 0, so the estimated R^2 and MAPE measure how well the model fits the data.

Following Berkman, Jacobsen, and Lee (2011), Liu and Matthies (2022), and Giglio and Xiu (2021), we construct our *War* factor, denoted as WarFac, as the innovation from an AR(1) model of *War*. We estimate the AR(1) process and compute the innovation on a rolling basis to avoid look-ahead bias.[14]

$$War_t = \rho_0 + \rho \times War_{t-1} + u_t \quad \text{and} \tag{3}$$

$$WarFac_t = u_t. \tag{4}$$

As a robustness check, we apply ARMA(1,1) and rolling regression to estimate the residuals and use them as WarFac. The results from ARMA(1,1) are a bit weaker, but of comparable statistical and economic significance. We report the results in Table E.2 in Appendix E.

4.3 Test Assets

We consider a large set of test assets constructed from a wide range of characteristics, including:[15,16]

1. 138 long-short anomaly portfolios from Hou, Xue, and Zhang (2020) (HXZ),
2. 1,372 single-sorted portfolios from HXZ,
3. 904 single-sorted portfolios from Chen and Zimmermann (2022) (CZ),
4. 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023),
5. Our own constructed 128 long-short anomaly portfolios based on HXZ,

[14]We start estimate the coefficients of the AR(1) process from 1926 to estimate the coefficients of the AR(1) process. The data on portfolio returns first became available in 1926. Our results are not sensitive to the different choices of this sample (see Table E.1).

[15]Lewellen, Nagel, and Shanken (2010) show that conventional double-sorted portfolios, exposed to a few characteristics, often present a low hurdle for asset pricing models due to their strong embedded factor structure.

[16]For all sets of test assets, we require the portfolios to have non-missing data from July 1972 to December 2016, so the number of portfolios used in our study may be smaller than that in the original papers.

6. Our own constructed 2,190 non-linear portfolios.[17]

To explore whether WarFac is an economy-wide factor that helps explain various anomaly portfolios, we include a variety of test assets, both traditional and complex, described below. Internet Appendix H describes the construction and the coverage of our test assets in detail.

We include groups of test assets in sequence. First, we start with test assets based on anomaly characteristics, including the 138 long-short portfolios from HXZ: momentum, value versus growth, investment, trading frictions, intangibles, and profitability. Second, we include all their 1,372 single-sorted portfolios from 1972 to 2016 to span a large return space. Third, we consider a different set of 904 single-sorted portfolios in CZ. Fourth, we include 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023). They argue that their ML-based nonlinear portfolios address critical problems of conventional sorts, including complex interactions, the curse of dimensionality, repackaging, and duplication. They conclude that the ML-based nonlinear portfolios present a new way of building better cross sections of portfolios that can be used in structural and reduced-form models. Fifth, we construct our characteristics-sorted portfolios according to the characteristics developed by HXZ. We use these portfolios as another test asset set for a robustness check. Finally, we build non-linear portfolios based on three polynomials. See Internet Appendix H.2 for a description of how these anomaly portfolios are constructed.

4.4 Contemporaneous Correlations between WarFac and Stock Returns

Before presenting pricing results, we report the contemporaneous correlation between WarFac and stock returns—for the market as a whole, for different industries, or for other traded factors, and the correlation during periods of high war risk as measured by high values of the war topic.

We report the result in Table D.1 in D. The correlation between WarFac and SMB is highest at 10.9%. WarFac has the lowest correlation with CMA (-13.4%), followed by MGMT (-12.4%) and FIN (-11.4%). *War* has low absolute correlations with other factors, with the absolute values under 10%. The correlation between *War* and market is only 5% both overall

[17] The data and code are available upon request from the authors. We will make them publicly available once the paper is accepted for publication.

and conditional upon war risk peak periods.

Across 12 Fama-French industry portfolios, WarFac has the highest correlation with Chemistry (4%), followed by Durables and Manufacturing. Overall, WarFac is only weakly correlated with industry portfolio returns.

4.5 Pricing Results: WarFac versus Factor Models

This subsection describes the pricing effectiveness of WarFac as compared with the factors in several well-known factor models: the Fama-French six-factor model (FF6), the Stambaugh and Yuan (2017) mispricing factor model (M4), the Daniel, Hirshleifer, and Sun (2020) composite behavioral and rational factor model (DHS), and the Hou et al. (2021) q-factor model (Q5). We examine several prominent models with different factors and motivations. FF6 is based on firm characteristics, M4 targets anomaly portfolios, DHS incorporates short- and long-term behavioral factors, and Q5 is grounded in an investment CAPM. We perform the two-pass test presented in equations (1) and (2) to estimate factor return premia and to assess model fit.

4.5.1 First Pass: Loadings

This section presents summary statistics of betas in the first-pass time series regressions of asset returns onto factors. We report the time period (T), number of test assets (N), average $|t|$ statistic of loadings, and the number of test assets with significant loadings (# Signif β). The significance of β is based on the $t = 1.65$ threshold corresponding to a 5% significance level for the one-sided test and a 10% significance level for the two-sided test. We also report the estimated return premium (λ) and associated t-statistics for a complete view. For comparison with other factors, we follow Giglio and Xiu 2021 and use the AR(1) innovations of non-tradable factors. Specifically, the table compares the following nontraded factors:

1. WarFac is the residual from rolling estimation of an AR(1) process on the *War* index.
2. CrisisFac is count-based crisis factor from Berkman, Jacobsen, and Lee 2011.
3. Ds16 and Dstop16 are stockholder consumption from Malloy, Moskowitz, and Vissing-Jørgensen (2009).
4. NI and HNI are news-based consumption from Liu and Matthies (2022).

5. Indp_Factor is the AR(1) innovation of the industrial production growth from McCracken and Ng (2016).
6. Macro_PC1, Macro_PC2, and Macro_PC3 are the VAR(1) innovations in the first three principle components of 127 macro variables from McCracken and Ng (2016).
7. LevFac is financial intermediary leverage factor from Adrian, Etula, and Muir (2014).

In terms of the number of significant loadings, for HXZ single-sorted, CZ single-sorted, tree-based, and our own constructed nonlinear portfolios, WarFac is ranked in the middle while Macro PC2 and HNI have a high number of assets with significant loadings. For HXZ long-short portfolios and our own anomalies, WarFac is associated with the highest number of assets with significant loadings.

WarFac is the only nontraded factor that commands significant negative return premia for *all* sets of test assets. Several factor models such as news-based consumption risk and Macro PC3 have a high number of significant β's but insignificant return premia in several test assets.

In summary, unlike other non-tradable factors, WarFac consistently demonstrates high number of significant loadings from the first pass and negative return premia for all sets of test assets in the second pass, as detailed in Table 1.

4.5.2 Second Pass: Return Premia for Factor Loadings

This section describes the result of the second-pass test and benchmarks the pricing power of WarFac against leading factor models. In the next section, we will compare WarFac with individual factors from those factor models. When other factors are included, the WarFac loadings are estimated in *multivariate* time-series regressions of excess asset returns onto WarFac and those factors.

The first set of test assets that we consider are the 138 long-short anomaly portfolios from HXZ in Panel A of Table 2. We examine the performance of WarFac on its own and then test whether introducing WarFac as an additional factor to the FF6, M4, DHS, and Q5 factor models provides incremental explanatory power.

In the first column with WarFac, the slope of the relation between returns and WarFac loadings is negative and significant at the 1% level ($t = -2.87$). Its monthly return premium is -1.33%. In a rational rare disaster risk setting, the negative sign implies that assets providing high returns during high war risk periods are good hedges of war risk and command a lower return premium. In a behavioral setting, the negative sign indicates that such assets are overpriced by investors who overweight the prospect of war.

WarFac maintains its significance even after introducing other factors to the model. Lewellen (2022) points out that including extra factors in a model, even ones that are not incrementally priced, can improve estimates of individual alphas and increase the power of asset-pricing tests by capturing contemporaneous return correlations.

In the last specification, when we include all factors from standard factor models, WarFac yields a return premium of -0.47%, significant at the 5% level. The introduction of WarFac to the FF6 factor model leads to an increase in the model explanatory power (R^2) of 12%. Adding WarFac to M4, DHS, and Q5 results in a respective increase in the explanatory power of 7%, 11%, and 1%. When considered as a solo factor, WarFac has an R^2 of 48% and a MAPE of 0.26%, while FF6, M4, DHS, and Q5 have R^2 of 59%, 65%, 51%, and 77% and MAPEs of 0.21%, 0.20%, 0.24%, 0.15%, respectively. These findings indicate that WarFac provides a good model fit even as a solo factor.

We next evaluate the performance of WarFac in pricing the 1,372 single-sorted portfolios from HXZ in Panel B of Table 2. The monthly return premium for WarFac is reduced by more than half, from -1.33% to -0.66%, and the absolute t-statistic diminishes from 2.87 to 2.25. This indicates that WarFac provides better pricing of the long-short anomaly portfolios. Furthermore, including WarFac in the factor models results in an increase of approximately 5.75% in their explanatory power. As a single-factor model, unsurprisingly, WarFac does not fit these portfolios as closely as multifactor models, as its R^2 is only 20% compared to 42%, 43%, 34%, and 55% provided by FF6, M4, DHS, and Q5, respectively. In the last column of Panel B, WarFac yields a return premium of -0.37%, significant at the 1% level, when tested against all factors. For this set of test assets, MAPEs of all models are around 0.086%.

Panel C reports the results for the 904 single-sorted portfolios of Chen and Zimmermann (2022). This set of test assets has become increasingly popular because it does not rely on any underlying benchmark factor model, such as FF6 or Q5. WarFac, as a solo factor, has a return premium of -1.26%, significant at the 1% level, and explains 22% of cross-sectional variation in expected returns of this set of assets. The return premium of WarFac remains significant at the 1% level after including other factor models or a model consisting of all other factors combined. Adding WarFac to DHS increases the R^2 from 12% to 23%.

When the test assets are the 360 ML-based nonlinear portfolios, WarFac yields a return premium of -3.32% per month and an insignificant common pricing error (intercept), as seen in the first column in Panel D of Table 2. Furthermore, including WarFac enhances the explanatory power (R^2) of the FF6, M4, DHS, and Q5 models by 34%, 24%, 29%, and 11%, respectively, and reduces the MAPEs of these models by 0.09% on average. For this set of test assets, the explanatory power of the WarFac as a single-factor model is 62%, which is higher than FF6 (41%), M4 (40%), DHS (35%), and Q5 (58%). Moreover, the addition of WarFac to the multifactor benchmark models substantially reduces the average cross-sectional pricing error or intercept from prominent factor models, from 3.25% to close to zero and insignificant on average. When all factors are included, WarFac has a return premium of 2%, significant at the 1% level.

These findings indicate that WarFac effectively prices various assets. Its advantage over other factor models is especially notable for the ML-based nonlinear portfolios. The ML-based nonlinear portfolios capture complex interactions among many characteristics and the nonlinear effects of characteristics on returns, making them more challenging to price than conventional sets of test assets.

To evaluate the robustness of our findings, we perform additional tests using our constructed long-short and nonlinear portfolios as test assets. Our 128 long-short anomaly portfolios are constructed similarly to those in HXZ. Our 2,190 nonlinear portfolios are constructed from the characteristics of up to three polynomials (see Internet Appendix H). The results of these additional test assets are reported in Table B.1 in Internet Appendix B. Overall, the results are robust to using these other test asset sets. WarFac is significant and provides the most additional information for pricing to DHS, followed by FF6, M4, and Q5.

In summary, we find that WarFac prices a wide range of test assets, and assets that pay off during high war risk periods are either overpriced on average or are good hedges, thereby earning low return premia. WarFac prices long-short and nonlinear portfolios very well. It contributes to the explanatory power of the benchmark models by approximately 25% when pricing 360 ML-based nonlinear portfolios and 7% when pricing 1,372 single-sorted and 128 long-short anomaly portfolios. This finding suggests that *War* is a valuable addition to the benchmark models for pricing a diverse range of assets.

4.5.3 Second Pass: WarFac versus Individual Factors

In the preceding subsection, we show that WarFac performs well in pricing a wide range of test assets as a solo factor. In this subsection, we examine whether any factor from benchmark factor models has similar pricing performance. To do so, we perform the two-pass tests with 15 individual factors, including WarFac, WarFac Mimicking Portfolios (henceforth WMP), and 13 traded factors from benchmark factor models. WMP is constructed using the cross-sectional approach proposed by Lehmann and Modest (1988) and applied by Cooper and Priestley (2011), for example. (See Section 6 for details).

Table 3 shows that WarFac and CMA (Conservative Minus Aggressive—an investment factor from FF6) are the only factors that consistently produce a significant return premium across all six sets of test portfolios. WMP prices almost all assets except our own constructed nonlinear portfolios. In 5 out of 6 sets of test assets (except our own constructed nonlinear portfolios), the R^2 produced by WarFac and WMP is higher than that of all traded factors. For the ML-based portfolios from Bryzgalova, Pelger, and Zhu (2023), WarFacs R^2 (62%) is more than double the largest R^2 produced by a traded factor (CMA at 28%). The MAPE results are consistent with those of R^2.

Overall, the results from Table 3 indicate that WarFac has stronger ability than traded factors to explain test portfolio returns.

5 *War* Discourse versus Other Uncertainty Indexes

This section tests whether WarFac has additional pricing power beyond other recently introduced news-based and event-based uncertainty indexes.

5.1 *War* Discourse versus Other Media-Based Uncertainty Indexes

The preceding section reports that *War* innovation negatively predicts returns across various test portfolios. Recent literature has introduced news-based disaster risks, most notably the news implied volatility (NVIX) from Manela and Moreira (2017) and the geopolitical risks (GPR) from Caldara and Iacoviello (2022). Specifically, Manela and Moreira (2017) also construct a news-based war index and show news events are positively associated with forward-looking volatility and equity risk premia. They construct news implied volatility (NVIX) from the front page of *WSJ* starting from 1890. To compare, we use their NVIX_War in this section.[18]

We investigate whether WarFac contains information beyond these two measures by performing horse-race cross-sectional return prediction tests. We perform cross-sectional tests with factors constructed from *War*, NVIX_War, and geopolitical risks (GPR). (Our tests use the square of NVIX_War to be consistent with the original paper. We rescale the factors constructed from GPR and NVIX_War to have the same standard deviation as WarFac to facilitate comparison.)

We construct these factors using Equation (4). As reported in Table 4, across all three sets of test assets, the return premium on WarFac remain negative and significant in the presence of NVIX_War and GPR factors, implying *War* contains distinct information. In the kitchen sink regression where we include WarFac, NVIX_War and GPR factors, the return premium is reduced by 17%, 28%, and 81% for WarFac, NVIX_War, and GPR factors, respectively, highlighting the distinct pricing power of WarFac. Meanwhile, NVIX_War commands a significant negative return premium only for the 360 ML portfolios, but yields a significant positive return premium for the CZ portfolios. GPR does not command any significant return premium across all test assets.

Overall, these findings indicate that WarFac is a cross-sectional return predictor, consistent with the predictions of the rare disaster models (Barro 2006; Gabaix 2012; Gourio 2008) or with overweighting of disaster risk, and contains valuable information not captured by other empirical measures of rare disaster risks.

5.2 *War* Discourse versus Crisis Event Counts: Pricing Industry Returns

We next investigate whether WarFac prices industry portfolios. Berkman, Jacobsen, and Lee (2011) measure empirical disaster risks by counting the number of crisis events each month.[19] They argue that the raw realized number of crisis events is a good proxy for investors' perception of rare disaster risks. The authors show that factors constructed from crisis event

[18] We thank the authors of these papers for making their data available.

[19] The data is updated to 2018 and is available at https://sites.duke.edu/icbdata/.

counts price the Fama-French 30 industry portfolios with negative return premiums. We examine here whether a news-based war factor, WarFac, has incremental predictive power beyond factors based on counts of crisis events.

Following Berkman, Jacobsen, and Lee (2011), we construct all event-based and news-based crisis-related factors as residuals from AR(1) processes on crisis event count, war event count, and our *War* index separately. Then, every month t, to estimate crisis betas, we run the time series regression of portfolio returns on the crisis factor and control for the market (MKT), size (SMB), and value (HML) factors as follows:

$$R^e_{i\tau} = \alpha_{it} + \beta_{it} X_\tau + \beta^{MKT}_{it} MKT_\tau + \beta^{SMB}_{it} SMB_\tau + \beta^{HML}_{it} HML_\tau + \epsilon_{i\tau}, \tag{5}$$

where $R^e_{i\tau}$ is the excess return of portfolio i over month $t - 59$ to month t, and X is either WarFac, the crisis event count factor (CrisisFac), or the war event count factor (CWarFac). To mitigate the effect of outliers on crisis betas, following Berkman, Jacobsen, and Lee (2011), each month, we cross-sectionally rank crisis betas β_{it} into quintiles and rescale the ranks so that the variable lies between 0 and 1. Next, to compute the monthly return premiums, we run the monthly cross-sectional regression of portfolio returns onto the previous month's betas computed in the previous step:

$$R^e_{it} = \lambda_{0t} + \lambda_t \beta_{i,t-1} + \lambda^{MKT}_t \beta^{MKT}_{i,t-1} + \lambda^{SMB}_t \beta^{SMB}_{i,t-1} + \lambda^{HML}_t \beta^{HML}_{i,t-1} + e_{it}, \tag{6}$$

where the λ_t are the estimates of factor return premiums in month t. Finally, to compute the unconditional factor return premiums, we take time-series averages of the λ_t and evaluate statistical significance using Newey and West (1987) standard errors.

In Panel A of Table 5, we use 30 industry portfolios as the test assets to be consistent with the original paper. The sample period is from July 1926, when the returns data are first available, to December 2018, the end of the crisis event sample. As in Table 9 of Berkman, Jacobsen, and Lee (2011), CrisisFac and CWarFac have negative monthly return premiums of about -0.3%. WarFac also yields a negative return premium of -0.24%, significant at the 5% level. In the last column, when we include all three crisis factors, both WarFac and CrisisFac have equal negative return premiums of about 0.3%, significant at the 5% level. In contrast, the return premium of CWarFac is only -0.23%, significant at the 10% level.

In Panel B, we evaluate a larger number of test assets—49 industry portfolios. For this set of test assets, when used alone, WarFac and CWarFac are insignificant, while CrisisFac yields return premiums of -0.24%, significant at the 5% level. The last column indicates that WarFac is associated with the largest return premium when all three crisis factors are included.

Overall, we find a factor based upon the news-based *War* variable prices industry portfolios with a negative return premium. This effect is strong and incremental to what is captured by the event-based crisis factors from previous literature.

6 The *War* Factor-Mimicking Portfolio

Our analysis so far constructs WarFac as a residual from an AR(1) process, where we avoid look-ahead bias by performing rolling forward regressions to estimate the AR(1) process. This is a computationally simple approach, but the resulting factor is non-traded. Non-traded factors may contain noise unrelated to returns. In general, such noise attenuates beta estimates of all assets in the first-pass time series regressions and inflates the return premium slope (market price of risk in rational settings) estimates in the second-pass cross-sectional regression (Adrian, Etula, and Muir 2014).

To address the noise issue associated nontraded factors, in this section, we form a traded version of the WarFac, which we call the WarFac mimicking portfolio. To verify robustness we use several approaches constructing the mimicking portfolio, and continue to use the abbreviation WMP to denote this portfolio.

WMP is in the form of a traded return. Overall, the results using WMP are consistent with our main results using the nontradable factor WarFac. A detailed description of our method, the results of spanning test, and pricing results are provided in Internet Appendix C.

7 Robustness Check: Return Premium of *War* Factor

Our pricing results so far are based on standard two-pass tests. To check the robustness of our results, in this section, we implement two recently introduced methods to identify factor risk premia: the protocol of factor identification of Pukthuanthong, Roll, and Subrahmanyam (2019) and the three-pass test of Giglio and Xiu (2021).

7.1 Protocol of Factor Identification

We now investigate the extent to which the WarFac Mimicking Portfolio (WMP) qualifies as a priced risk factor by the criteria set forth by Pukthuanthong, Roll, and Subrahmanyam (2019). The protocol argues the true priced risk factor should meet two criteria: (1) it is related to the SDF and (2) it can price assets. The first stage provides a sequence of steps representing the necessary conditions for factor candidates to be valid.[20] The second suggested stage entails testing whether factor candidates that satisfy the necessary conditions are pervasive or instead are unpriced in the cross-section. We present a detailed exposition of these criteria in Internet Appendix F.[21]

The protocol of factor identification applies only to tradable factors. Hence, to use the protocol, a nontraded factor such as WarFac must be converted into a tradable version by constructing a mimicking portfolio. As reported in Table F.1 and Table F.2, WMP passes these conditions, consistently being a priced risk factor.

7.2 Three-Pass Test

The two-pass test has two limitations. First, it does not address omitted variable bias when relevant factors are not included. Second, when there is a measurement error of the factor, the test becomes difficult to estimate. This problem is more common when factors are not tradable. To overcome these limitations, Giglio and Xiu (2021) propose a three-pass test to estimate an observable factor's risk premium.

The test has three steps. First, a principal component analysis is performed to extract an optimal number of latent factors spanning the return space of a given set of test assets. Second, the risk premia of these latent factors are estimated via a cross-sectional regression of average asset returns onto asset exposures to these latent factors. Third, the observable factor is regressed onto the latent factors via a time-series regression. The product of the risk premia of latent factors estimated in the second step and the slopes of the time-series regression from the third step identifies the risk premia of the observable factor. Giglio and

[20] A candidate that does not satisfy these conditions is not a priced risk factor, but could represent an abnormal profit opportunity for investors.

[21] Surpassing these hurdles makes it more plausible that the factor's performance reflects priced risk. However, it does not rule out the possibility that its performance derives from behavioral effects (i.e., market inefficiency).

Xiu (2021) apply their three-pass test to a set of traded and non-traded factors and find that most non-traded factors are not priced in a large cross section of asset returns because they contain a lot of noise.

We apply the three-pass test to WMP and other traded factors from the four prominent factor models discussed above and report the results in Table G.1. WMP has a significant return premium across all assets except single-sorted portfolios. MOM is the only factor that is significant for all assets. The other factors are insignificant for at least two test assets. Even though other traded factors do not consistently yield significant estimated return premia across all sets of test assets, for all of the factors across all test assets, we reject the null that they are weak factors according to the test of weak factors proposed by Giglio and Xiu (2021) (reported in the last row of each panel of Table G.1).

Overall, the three-pass test results and the protocol for factor identification reported in the previous subsection are consistent with WMP and MOM being priced risk factors for all test assets studied in this paper.

7.3 The Variants of Seed Words and Number of Topics

In our main tests, we apply the most parsimonious approach for *War*, which is to use only one seed word. Here we examine whether the results are robust to variations in the seed words and the numbers of topics. These are the key inputs to the sLDA method that we apply.

First, we present the results based on the same five seed words of *War* used by Hirshleifer, Mai, and Pukthuanthong (2024) while keeping the number of topics at 15 topics (14 seeded plus one unseeded topic). Second, "terrorism" might have a connection with a potential war risk, especially since the 9/11 attacks. However, such a strong association might not exist in the late 1800s or early 1900s. Thus, we modify the group of seed words of *War* and exclude "terrorism" and "terrorist." Third, we add another disaster-related topic—*Natural Disaster*, which includes seed words such as "earthquake, flood," and "hurricane," while enhancing our *Pandemic* topic by increasing the number of seed words from 2 ("epidemic" and "pandemic") to 12 and keeping the seed words for other topics unchanged. The updated list of seed words for this specification in reported in Table E.3. This could affect our results if these "disaster-like" topics use words that are correlated with *War*. As reported in Table E.3, WarFac is still associated with significant and negative return premia.

We next experiment with further modifications of seed words and a number of topics: increasing the number of seed words for *War* while maintaining the other topics; modifying the seed words for *War* and removing duplicates in seed words within and across topics; and increasing the number of unseeded topics from 1 to 50. As an extreme, we also experiment with including only one seeded topic for *War* with only one seed word "war" together with 50 unseeded topics.[22]

We find the results for *War* remain robust across these specifications. See Table E.3 in Appendix E for the results. We find the return premium of WarFac remains significant statistically and economically Regarding MAPE, Table E.3 shows that across six test assets, WarFac based on a single seed word ("war"), three seed words ("war, conflict, tension"), or five seed words ("war, conflict, tension, terrorism, terrorist") has average MAPEs of 0.23%, 0.27%, and 0.23%, respectively. WarFac with one seed word of "war" exhibits a similar MAPE to that of WarFac with five seed words, while avoiding the concern of subjective seed word selection.

7.4 Comparing sLDA with LDA

This section compares WarFac constructed by sLDA with that by LDA. An unsupervised LDA model can automatically determine words for best in-sample fit instead of being constrained to predetermined words. This should help unsupervised LDA achieve a better fit in-sample, when estimating on the entire dataset. However, estimating with the full dataset generates look-ahead bias. Owing to the possibility of overfitting, it is much less clear whether unsupervised LDA will have greater forward-looking predictive power than sLDA. As is standard in machine learning, there is a trade-off between using weaker constraints to achieve a better fit, versus stronger constraints to avoid overfitting.[23]

[22]We thank an anonymous referee for suggesting the seed words for *Pandemic*. To identify the seed words above for *Natural Disasters*, we searched articles on https://www.nature.com/ that have *Natural Disasters* as keywords and subjects. Then, based on informal examination, we identified distinctive words relevant for this topic used in those articles. The additional seed words listed above for the *War* robustness checks are based on intuitive plausibility.

[23]Also, users of unsupervised LDA still need to specify the number of topics. In practice, users normally choose the optimal number of topics by maximizing statistical measures such as empirical likelihood or perplexity using cross-validation on the whole dataset, introducing possible look-ahead bias.

In addition to avoiding look-ahead bias, sLDA has the further advantage over unsupervised LDA of accommodating semantic shifts over time. See the discussion on p. 12. This is crucial for analyzing a textual dataset spanning 150 years. Empirically, we find that WarFac prices assets more effectively than unsupervised LDA.

For unsupervised LDA, we use the topics constructed by Bybee et al. (2024).[24] Since Bybee et al. (2024) do not have any topic focusing only on war, we use the average of scores for their topics related to war (see the list on footnote 8) as a war index. We create a factor defined as the AR(1) innovation of the averaged score, estimated on a rolling monthly basis. We also construct two additional factors, Financial Crisis and Recession, using the same approach. Bybee et al. (2024) find that these factors are the most significant in predicting economic variables. (We rescale these unsupervised factors to have the same standard deviation as WarFac.)

We include four factors in the two-pass test, including WarFac, unsupervised war factor, Financial_Crisis, and Recession factors. We report the results in Table D.3. We find the factors constructed on the topics from unsupervised machine learning do not price assets in a univariate test in columns (2) to (4) and a kitchen sink test in column (5). In contrast, WarFac prices all test assets in the sense that it is associated with a negative and significant return premium in both types of test. We also find that the Recession factor is associated with a weak positive return premium for some test assets. (This is counterintuitive since a rational risk argument implies that the Recession factor would have a negative risk premium. Assets that pay off during recession periods are good hedges, implying low expected returns). See Table D.3 in Appendix D for the results.

8 Economic Sources of the War Return Premium

8.1 Is War Risk Another Tail Risk?

The literature has established that tail risk is priced. In this section, we identify which tail risks exactly investors are worried about.

We perform the two-pass test comparing war risk with the other betas that capture

[24]The topic weight data is available from the paper's companion website.

downside risk.[25] We form mimicking portfolios of these betas by buying the top decile and selling the bottom decile sorted using stock-level betas.

When we include all of these tail risk mimicking portfolios together with WarFac, the WarFac return premium remains significant, suggesting WarFac presents a distinct risk that is not subsumed by other downside risks and it is a downside risk that investors are concerned about. Notably, under HXZ single-sorted portfolios, WarFac is the only factor with a significant beta return premium. These results, detailed in Table D.2 in Appendix D, underscore the market's concern about WarFac even after controlling other types of extreme risks.

8.2 Does Analytical News Drive the Results?

In this section, we investigate whether the pricing power of *War* is driven by factual news or by analytical news about war. If it is factual news, the interpretation of our results is more straightforward.

To examine this issue, we identify the month with the most negative return premium of WarFac averaged across six test assets, which turns out to be February 2001.[26] We then count the number of war-related and analytical-related words for each article in that month. The count of war-related words is the product of the *War* topic weight and total number of words. We perform a simple correlation between the count of war-related words and of analytical-related words. Additionally, to normalize we examine the correlation between

[25]The betas are available on a monthly basis. They include CAPM beta, bear beta (Lu and Murray 2019), downside beta (Ang, Chen, and Xing 2006), relative downside beta (Ang, Chen, and Xing 2006), VIX beta (Ang et al. 2006), volatility beta (Cremers, Halling, and Weinbaum 2015), jump beta (Cremers, Halling, and Weinbaum 2015), co skewness beta (Harvey and Siddique 2000), skewness beta (Chang, Christoffersen, and Jacobs 2013), tail beta (Kelly and Jiang 2014), and idiosyncratic volatility beta (Ang et al. 2006).

[26]Our regression is from 1972 (based on the availability of all test assets). February 2001 seems to be attributed to Middle Eastern tensions. During this time, there were ongoing tensions in the Middle East, particularly between Israel and Palestine. The Second Intifada, a period of intensified Israeli-Palestinian conflict, began in late 2000 and continued through 2001. Such geopolitical tensions often contribute to increased perceptions of war risk globally. Also, it was at the time of a U.S. political transition. February 2001 marked the early months of George W. Bush's presidency in the United States. Transitions in major world powers can bring uncertainty about foreign policy, affecting global risk perceptions about potential military engagements or shifts in international alliances. There were also political tensions in the Korean Peninsula, ongoing issues in the Balkans following the conflicts of the 1990s, and other regional instabilities.

these word counts adjusted for total word count.[27,28]

We find that the total number of war-related and analytical words within articles are positively correlated, with significance at the 1% level. However, using the proportion of these words relative to the total number of words in the article, the correlation weakens and becomes statistically insignificant. In November 2000, a month with the second highest WarFac return premium, this pattern of insignificance in proportional relevance was also observed.

Given the mixed results—significant correlations in raw word counts but not in proportions—we conclude that the evidence is inconclusive about whether the pricing power of WarFac is directly influenced by the coverage of opinions on war.

8.3 Does Other News Influence the Pricing Power of War Risk?

This section examines whether other news topics influence the return premium of WarFac during the upswings and downturns of market attention to war. Increases in *War* typically align with specific events, but the drivers of its decreases are less clear. Decreases may stem from international tensions that dissipate quietly, or shifts in focus due to unrelated disturbances. To distinguish the effects of up and down movements in *War*, we define two dimensions of WarFac, which we call WarFac^+ and WarFac^-. WarFac^+, derived from positive AR(1) innovations of *War*, reflects the market attention to an increase in coverage of war news. WarFac^- captures the market attention to a decrease in war-related news. Such a decrease may indicate decreased concerns about war, or, alternatively, a diverted of attention away from war because of salient news about other issues.

We obtain several results. First, both WarFac^+ and WarFac^- price assets in the market.

[27] We asked ChatGPT 4.0 for analytical-related words. The words provided include "analysis, argument, assessment, column, columnist, comment, commentary, critique, debate, editor_note, editorial, essay, examination, from_the_editor, hot_take, insight, musing, opinion, outlook, perspective, point_of_view, reflection, review, special_report, take, think_piece, thought," and "viewpoint." "perspective" and "outlook" suggest a forward-looking or interpretive angle on news events; "thought" and "musing" are more informal terms used in opinion pieces that take a personal or reflective tone; "analysis" is used to denote an analytical piece; "take" and "hot_take" are more informal terms that can be used, especially in more modern or conversational opinion pieces; "editor_note" and "from_the_editor" indicate an editorial perspective or opinion; and "special_report" sometimes is used for in-depth analytical pieces or more objective report.

[28] The version is ChatGPT 4.0 and the prompts are "What are the key words in opinion or analytical articles/columns in the news?" and "Besides these keywords, "Opinion," "Editorial," "Analysis," "Commentary," "op-ed," or "Perspective," is there anything else?" made in December 14, 2023.

WarFac$^-$ prices HXZ long-short and single-sorted portfolios and CZ portfolios, as well as our own constructed anomaly-based portfolios. However, WarFac$^+$ prices the ML-based portfolios and our nonlinear portfolios better than WarFac$^-$. See Table E.2 in Appendix E.

Second, it is possible that downward movements in *War* do not derive primarily from war-related news. They may be may instead be driven by the arrival of salient news about other topics that shifts attention away from war. In an efficient market, the fact that some other topic catches attention should not distract investors from fully incorporating the information contained in news about *War*. This suggests that if WarFac$^-$ does not reflect any actual news about war itself, an efficient market may not offer a return premium for WarFac$^-$. In a similar spirit, the return premium on WarFac$^-$ may be eliminated after controlling for factors constructed from other news topics. In contrast, in a behavioral setting, a shift of attention away from war deriving from distraction may affect the market pricing of war risk.

The first possibility is rejected since we find that both WarFac$^+$ and WarFac$^-$ both have significant return premia. For the second possibility, we examine by controlling for factors from other discourse topics in the two-pass test. We find that return premium of WarFac$^-$ remains significant except for the tree portfolios (see Table D.5).

Taken together, these findings suggest that the return premium of WarFac is distinct and is not heavily influenced by non-war news.

9 Conclusion

This paper constructs a war factor based on the measure of *War* media textual discourse proposed by Hirshleifer, Mai, and Pukthuanthong (2024) to evaluate predictions of theories of rare disaster risk and behavioral theories of the mispricing of factors when investors overweight the prospect of rare disasters. We find that loadings on the war factor, WarFac, strongly predict the cross section of stock returns and provide strong incremental predictive power relative to existing factor models. These findings apply across a broad range of test assets.

The return premium for loadings on WarFac is negative. In a rational asset pricing approach in which investors dislike rare disasters, investors value the hedge provided by assets that pay off more when the risk of war is greater. In such a setting, the higher the factor loading, the less risky the stock, implying a lower expected return.

Our findings are also consistent with behavioral-based approaches, such as a setting in which investors overestimate the probability of war owing to the salience of rare disasters, or in which investors overweight low probabilities as in cumulative prospect theory. Such overweighting of war prospects implies undervaluation of stocks negatively sensitive to war risk and overvaluation of positively sensitive stocks. Thus, stocks with high loadings on WarFac should have low expected returns.

Our evidence suggests that *War* is not subsumed by the news-implied volatility (NVIX) of Manela and Moreira (2017) and the geopolitical risk (GPR) of Caldara and Iacoviello (2022). WarFac receives a significant negative return premium even when all factors, such as FF6, M4, Q5, and DHS, are included in the same regression. This finding is consistent with the prediction of Gabaix (2012) that equities that provide good returns during high-risk periods of rare disasters require lower returns to compensate for the risk cross-sectionally.

We find that the return premium associated with WarFac is distinct from and strong after controlling for other tail risk factors. This may be because of the profoundly catastrophic nature of war for economic fundamentals, or to unique visceral psychological reactions by investors to war risks.

We find that both upward and downward innovations in attention to war is associated with return premia. After controlling for factors derived from other discourse topics, the return premium of WarFac generally remains strong. The war return premium is driven by factual news rather than opinion articles. Our findings support the notion that rare disasters are important for asset pricing, either because they imply large rational risk premia or because investors tend to overweight the prospect of rare disasters. Our results further imply that a particular kind of disaster, war, is crucial for explaining the cross section of expected stock returns.

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Figure 1. Estimation Scheme

This figure plots the rolling estimation scheme for the sLDA model. Every month t, news articles in the previous 120 months (including month t) are used to estimate the sLDA model, and then articles in month t are used to compute topic weights in that month.

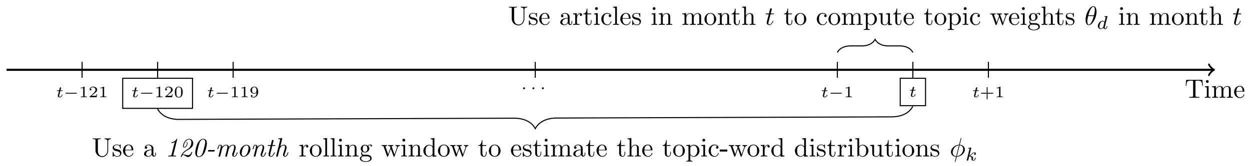


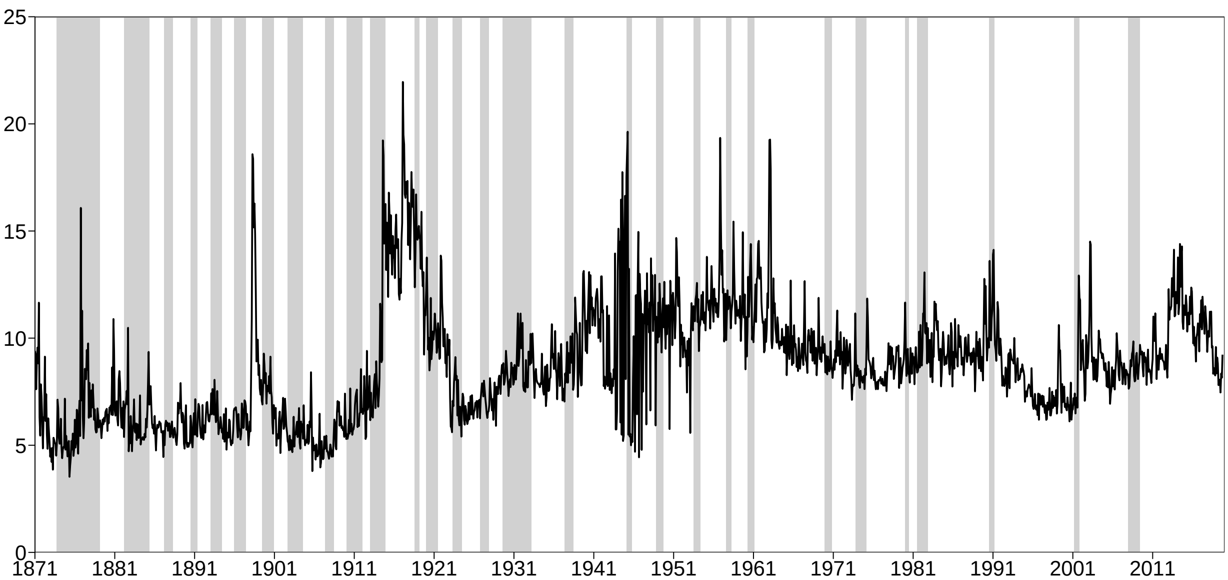
Figure 2. Narrative Contents

This figure plots the frequencies of n-grams related to *War* over time. Frequencies are constructed according to the sLDA model described in Section 2, and the size of each n-gram indicates its frequency. The sample period is from January 1871 to October 2019.

Figure 3. Time Series of the *War* Index

This figure plots the time series of the *War* Risk index constructed according to the sLDA model described in Section 2. The gray-shaded areas represent NBER-defined recessions. Panel A plots the index from January 1871 to October 2019, and Panel B the ten articles that have contributed significantly to ten monthly heights of *War* from January 1990 to October 2019.

Panel A: 1871-2019



Panel B: 1990-2019

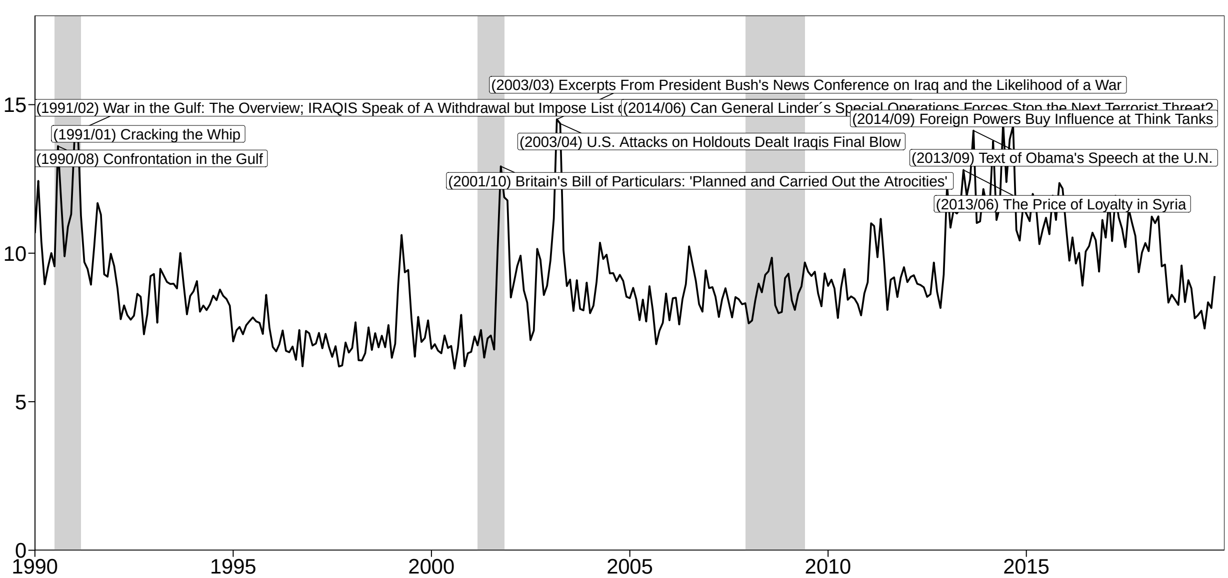


Table 1
Betas and Return Premia for Non-Traded Factors

This table reports the statistics for the betas in first-pass time-series regressions of asset returns onto non-traded factors. Statistics include average of absolute betas (avg($|t|$) and number of betas having absolute values above 1.65 (# Signif β). Also reported are the estimates of return premium and t-statistic computed with Shanken (1992) correction in the second-pass cross-sectional regressions of average asset returns on factor betas. Nontraded factors include WarFac (rolling AR(1) residuals of *War*); consumption factors (Ds12 and Dstop16) from Malloy, Moskowitz, and Vissing-Jørgensen (2009); news-based consumption factors (NI and HNI) from Liu and Matthies (2022); industrial production factor (Indp_Factor); the first three principal components of macroeconomic variables (Macro_PC1, Macro_PC2, and Macro_PC3) from McCracken and Ng (2016); and financial intermediary factor (LevFactor) from Adrian, Etula, and Muir (2014). Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D, own constructed anomaly portfolios in Panel E, and own constructed nonlinear portfolios in Panel F. N is the number of test assets and T is the number of months. The overall sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table 1
Betas and Return Premia for Non-Traded Factors (Cont.)

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

Factor	T	N	avg($\|t\|$)	# Signif β	λ	t_λ
WarFac	532	138	1.21	42	-1.33	-2.87
CrisisFac	532	138	0.63	6	1.50	2.31
Ds16	228	138	0.74	13	0.42	1.42
Dstop16	228	138	1.07	31	1.35	2.20
NI	496	138	0.97	26	0.96	2.39
HNI	496	138	0.75	6	-0.30	-1.19
Indp_Factor	532	138	0.73	12	0.59	1.84
Macro_PC1	532	138	0.87	21	0.25	0.60
Macro_PC2	532	138	0.75	8	0.20	0.58
Macro_PC3	532	138	0.87	17	-0.59	-1.87
LevFactor	448	138	1.09	30	0.84	2.66

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

Factor	T	N	avg($\|t\|$)	# Signif β	λ	t_λ
WarFac	532	1372	1.13	164	-0.66	-2.25
CrisisFac	532	1372	0.85	13	0.47	1.93
Ds16	228	1372	0.43	0	0.05	0.29
Dstop16	228	1372	0.58	3	0.56	1.59
NI	496	1372	1.79	869	0.69	3.66
HNI	496	1372	1.61	615	-0.04	-0.21
Indp_Factor	532	1372	1.15	81	0.22	1.54
Macro_PC1	532	1372	1.24	155	0.02	0.09
Macro_PC2	532	1372	1.88	980	0.20	1.10
Macro_PC3	532	1372	1.18	107	-0.20	-0.80
LevFactor	448	1372	0.88	46	0.48	1.94

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

Factor	T	N	avg($\|t\|$)	# Signif β	λ	t_λ
WarFac	532	904	1.24	116	-1.26	-3.16
CrisisFac	532	904	0.59	0	1.33	1.58
Ds16	228	904	0.50	1	0.38	0.78
Dstop16	228	904	0.36	2	1.00	1.68
NI	496	904	1.21	188	-0.23	-0.67
HNI	496	904	1.10	60	-0.61	-2.17
Indp_Factor	532	904	0.85	6	0.85	2.66
Macro_PC1	532	904	1.14	24	0.69	1.74
Macro_PC2	532	904	1.52	306	-0.20	-0.79
Macro_PC3	532	904	1.70	572	0.05	0.13
LevFactor	448	904	0.89	20	0.66	1.94

Table 1
Betas and Return Premia for Non-Traded Factors (Cont.)

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

Factor	T	N	avg($\|t\|$)	# Signif β	λ	t_λ
WarFac	532	360	0.99	56	-3.32	-3.42
CrisisFac	532	360	0.65	0	4.12	1.83
Ds16	228	360	0.33	0	-3.12	-2.12
Dstop16	228	360	0.56	0	0.96	1.26
NI	496	360	0.94	70	-1.21	-2.15
HNI	496	360	0.88	39	-2.39	-3.11
Indp_Factor	532	360	0.64	0	0.58	1.42
Macro_PC1	532	360	1.19	21	2.79	1.69
Macro_PC2	532	360	1.25	98	0.13	0.36
Macro_PC3	532	360	1.76	242	0.19	0.40
LevFactor	448	360	0.66	4	2.02	3.47

Panel E: Own Constructed Anomalies

Factor	T	N	avg($\|t\|$)	# Signif β	λ	t_λ
WarFac	532	128	1.25	42	-1.02	-2.12
CrisisFac	532	128	0.72	8	0.63	1.03
Ds16	228	128	0.80	11	-0.11	-0.32
Dstop16	228	128	1.07	29	0.91	1.45
NI	496	128	0.75	13	0.99	2.38
HNI	496	128	0.70	6	0.83	2.10
Indp_Factor	532	128	0.81	13	0.03	0.08
Macro_PC1	532	128	0.89	18	0.34	0.82
Macro_PC2	532	128	0.68	3	1.40	2.03
Macro_PC3	532	128	0.94	19	-0.11	-0.26
LevFactor	448	128	1.23	33	0.41	1.57

Panel F: Own Constructed Nonlinear Portfolios

Factor	T	N	avg($\|t\|$)	# Signif β	λ	t_λ
WarFac	532	2190	1.17	78	-0.89	-3.64
CrisisFac	532	2190	0.63	0	1.01	1.32
Ds16	228	2190	0.49	0	-0.07	-0.14
Dstop16	228	2190	0.25	0	0.52	0.87
NI	496	2190	0.98	35	0.30	0.88
HNI	496	2190	0.92	1	-0.11	-0.58
Indp_Factor	532	2190	0.75	0	0.79	2.92
Macro_PC1	532	2190	1.12	4	0.35	2.09
Macro_PC2	532	2190	1.44	361	-0.26	-1.59
Macro_PC3	532	2190	1.80	1826	-0.37	-0.86
LevFactor	448	2190	0.85	2	0.61	1.55

Table 2
War Factor and Return Premium

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premia. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. "WarFac" is rolling AR(1) residuals of *War*; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD, FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_MKT, R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.18 ***	0.16 ***	0.15 ***	0.09 ***	0.10 ***	0.18 ***	0.12 ***	0.13 ***	0.09 **	0.09 ***	0.06 ***
	(2.97)	(7.08)	(4.81)	(3.23)	(3.00)	(2.80)	(3.95)	(3.20)	(2.20)	(2.69)	(2.88)
WarFac	-1.33 ***					-1.40 ***	-1.21 ***	-1.01 ***	-1.14 ***	-0.55 ***	-0.47 **
	(-2.87)					(-3.41)	(-4.52)	(-3.95)	(-4.05)	(-2.70)	(-2.45)
MKT		0.48	0.89 **	1.14 ***		-0.22	0.21	0.51	1.07 **		0.61 *
		(1.50)	(2.51)	(2.98)		(-0.47)	(0.51)	(1.21)	(2.19)		(1.80)
SMB		0.05	-0.02				0.01	-0.06			0.16
		(0.30)	(-0.15)				(0.03)	(-0.31)			(0.90)
HML		0.27					0.29				0.55 ***
		(1.60)					(1.41)				(3.17)
RMW		0.28 **					0.23				0.21
		(2.27)					(1.57)				(1.63)
CMA		0.54 ***					0.52 ***				0.20 *
		(4.91)					(4.01)				(1.70)
MOM		0.61 ***					0.72 ***				0.48 **
		(2.91)					(3.20)				(2.22)
MGMT			0.71 ***					0.65 ***			0.72 ***
			(4.50)					(3.61)			(4.00)
PERF			0.47 *					0.52 *			-0.13
			(1.93)					(1.86)			(-0.49)
PEAD				0.36 **					0.35		0.39 ***
				(2.19)					(1.64)		(2.62)
FIN				0.96 ***					0.90 ***		0.86 ***
				(4.64)					(3.80)		(3.77)
R_MKT					0.66 *					0.51	
					(1.87)					(1.43)	
R_ME					0.25					0.27	0.29 *
					(1.48)					(1.54)	(1.76)
R_IA					0.44 ***					0.41 ***	0.36 ***
					(3.66)					(3.33)	(2.99)
R_ROE					0.33 **					0.35 **	0.43 ***
					(2.40)					(2.52)	(3.18)
R_EG					0.80 ***					0.70 ***	0.79 ***
					(6.05)					(4.88)	(6.63)
R^2	48	59	65	51	77	48	71	72	62	78	81
MAPE	0.26	0.21	0.20	0.24	0.15	0.26	0.17	0.17	0.20	0.15	0.13
N	138	138	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532	532	532

Table 2
War Factor and Return Premium (Cont.)

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.76 ***	0.43 **	0.25	-0.22	0.35	0.80 ***	0.50 **	0.32	-0.28	0.39	0.32
	(3.79)	(2.12)	(1.11)	(-0.81)	(1.55)	(2.87)	(2.10)	(1.24)	(-0.96)	(1.63)	(1.45)
WarFac	-0.66 **					-0.62 ***	-0.61 ***	-0.53 ***	-0.51 ***	-0.40 ***	-0.37 ***
	(-2.25)					(-5.16)	(-5.40)	(-4.45)	(-4.26)	(-4.18)	(-3.98)
MKT		0.16	0.34	0.84 **		-0.18	0.10	0.28	0.91 **		0.29
		(0.55)	(1.08)	(2.47)		(-0.53)	(0.31)	(0.82)	(2.51)		(0.96)
SMB		0.16	0.20				0.12	0.14			0.19
		(1.08)	(1.31)				(0.78)	(0.93)			(1.26)
HML		0.30 **					0.33 **				0.49 ***
		(1.98)					(2.08)				(3.18)
RMW		0.18					0.20 *				0.16
		(1.56)					(1.67)				(1.40)
CMA		0.20 **					0.24 **				0.19 *
		(2.06)					(2.41)				(1.94)
MOM		0.58 ***					0.63 ***				0.44 **
		(2.84)					(3.02)				(2.17)
MGMT			0.46 ***					0.48 ***			0.38 **
			(2.89)					(2.93)			(2.54)
PERF			0.47 **					0.48 **			0.28
			(2.12)					(2.11)			(1.29)
PEAD				0.32 **					0.31 *		0.35 ***
				(2.13)					(1.92)		(3.06)
FIN				0.57 ***					0.61 ***		0.56 ***
				(2.84)					(2.96)		(2.84)
R_MKT					0.24					0.21	
					(0.77)					(0.65)	
R_ME					0.34 **					0.34 **	0.27 *
					(2.29)					(2.28)	(1.87)
R_IA					0.27 **					0.28 **	0.27 ***
					(2.43)					(2.40)	(2.76)
R_ROE					0.23 *					0.26 **	0.38 ***
					(1.76)					(2.00)	(3.03)
R_EG					0.61 ***					0.55 ***	0.60 ***
					(5.65)					(5.08)	(6.13)
R^2	20	42	43	34	55	20	50	49	40	58	65
MAPE	0.11	0.09	0.09	0.09	0.08	0.11	0.08	0.08	0.09	0.08	0.07
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532	532	532

Table 2
War Factor and Return Premium (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	1.16 ***	0.93 ***	0.76 ***	1.59 ***	0.65 ***	1.34 ***	0.74 ***	0.55 ***	1.23 ***	0.57 ***	0.41 *
	(3.68)	(5.93)	(4.76)	(7.04)	(3.28)	(3.71)	(3.59)	(2.64)	(4.10)	(2.78)	(1.79)
WarFac	-1.26 ***					-1.09 ***	-1.17 ***	-1.07 ***	-1.14 ***	-0.78 ***	-0.74 ***
	(-3.16)					(-2.70)	(-4.72)	(-3.89)	(-4.43)	(-3.25)	(-3.50)
MKT		-0.40	-0.24	-0.77 ***		-0.45	-0.16	0.06	-0.32		0.18
		(-1.56)	(-0.91)	(-2.69)		(-0.98)	(-0.55)	(0.20)	(-1.00)		(0.60)
SMB		0.35 **	0.47 ***				0.15	0.18			0.14
		(2.32)	(3.00)				(0.95)	(1.21)			(0.83)
HML		0.30 **					0.35 **				0.58 ***
		(2.05)					(2.13)				(3.47)
RMW		-0.02					0.29 **				0.02
		(-0.11)					(2.12)				(0.16)
CMA		0.84 ***					0.66 ***				0.40 ***
		(7.00)					(4.98)				(2.90)
MOM		0.56 **					0.82 ***				0.71 ***
		(2.48)					(3.44)				(3.03)
MGMT			0.66 ***					0.85 ***			0.68 ***
			(3.84)					(4.47)			(3.71)
PERF			0.58 **					0.76 ***			1.01 ***
			(2.39)					(2.60)			(4.31)
PEAD				-0.04					0.08		0.37 *
				(-0.20)					(0.28)		(1.79)
FIN				0.24					0.61 **		1.41 ***
				(1.10)					(2.48)		(5.25)
R_MKT					-0.03					0.06	
					(-0.11)					(0.21)	
R_ME					0.40 ***					0.39 **	0.36 **
					(2.60)					(2.49)	(2.35)
R_IA					0.42 ***					0.45 ***	0.64 ***
					(2.58)					(2.74)	(4.21)
R_ROE					0.20					0.39 **	0.86 ***
					(1.04)					(2.07)	(4.72)
R_EG					1.48 ***					1.31 ***	1.69 ***
					(8.02)					(6.97)	(10.31)
R^2	22	41	43	12	57	23	48	52	23	60	65
MAPE	0.18	0.14	0.14	0.19	0.12	0.18	0.13	0.13	0.18	0.12	0.11
N	904	904	904	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532	532	532	532

Table 2
War Factor and Return Premium (Cont.)

Panel D: ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	1.20	3.39 ***	3.28 ***	4.22 ***	2.11 ***	1.69	-0.04	1.11	0.86	0.72	-0.07
	(1.19)	(6.80)	(7.51)	(6.07)	(2.73)	(1.59)	(-0.03)	(1.26)	(0.69)	(0.73)	(-0.07)
WarFac	-3.32 ***					-3.08 **	-4.18 ***	-3.19 ***	-3.46 ***	-3.60 ***	-2.06 ***
	(-3.42)					(-2.14)	(-3.70)	(-4.00)	(-3.89)	(-3.94)	(-3.71)
MKT		-3.39 ***	-3.24 ***	-3.86 ***		-1.16	0.46	-0.64	-0.22		0.30
		(-6.06)	(-6.40)	(-5.47)		(-0.86)	(0.38)	(-0.71)	(-0.19)		(0.32)
SMB		0.18	0.12				-0.61 **	-0.90 ***			-0.10
		(1.04)	(0.64)				(-2.00)	(-3.33)			(-0.43)
HML		1.31 ***					0.72				0.71 *
		(6.24)					(1.57)				(1.85)
RMW		0.20					1.60 ***				0.59
		(0.95)					(3.05)				(1.55)
CMA		0.28 *					0.10				0.37
		(1.81)					(0.22)				(1.14)
MOM		0.21					1.13 ***				1.05 ***
		(0.86)					(2.66)				(3.22)
MGMT			1.32 ***					1.35 ***			-0.42
			(7.13)					(3.55)			(-0.99)
PERF			0.03					0.62			1.62 **
			(0.11)					(1.08)			(2.40)
PEAD				-0.56 **					0.01		0.15
				(-2.09)					(0.01)		(0.24)
FIN				0.83 **					1.90 ***		2.34 ***
				(2.54)					(3.04)		(3.06)
R_MKT					-1.76 **					-0.19	
					(-2.17)					(-0.19)	
R_ME					-0.15					-0.18	0.24
					(-0.66)					(-0.58)	(0.96)
R_IA					0.24					0.47	0.14
					(0.93)					(1.34)	(0.39)
R_ROE					-0.17					0.96 **	2.30 ***
					(-0.41)					(2.17)	(3.92)
R_EG					3.39 ***					1.10	3.32 ***
					(5.95)					(1.43)	(5.89)
R^2	62	41	40	35	58	63	75	64	64	69	88
MAPE	0.44	0.49	0.49	0.53	0.45	0.44	0.33	0.43	0.45	0.41	0.22
N	360	360	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532	532	532

Table 3
War Factor versus Individual Traded Factors

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta_{if}\lambda + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the factor exposure of portfolio i estimated via a time-series regression of portfolio return onto factor, and λ_f is the factor return premium. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D, own constructed anomalies in Panel E, and own constructed nonlinear portfolios in Panel F. "WarFac" is the innovations in *War* and "WMP" is the mimicking portfolio of WarFac; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD, FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_MKT, R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	0.18 ***	0.23 ***	0.21 ***	0.21 ***	0.25 ***	0.18 ***	0.17 ***	0.26 ***	0.23 ***	0.18 ***	0.19 ***	0.20 ***	0.25 ***	0.17 ***	0.15 ***
	(2.97)	(5.33)	(5.61)	(6.08)	(6.58)	(6.33)	(4.98)	(6.64)	(5.95)	(6.04)	(6.57)	(5.27)	(6.34)	(5.81)	(4.70)
Factor	-1.33 ***	-3.12 ***	-0.87 ***	-0.22	0.38 **	0.37 *	0.31 **	0.37 ***	0.51 ***	0.32	0.18	0.64 ***	0.38 ***	0.22	0.34 ***
	(-2.87)	(-3.92)	(-2.77)	(-1.26)	(2.56)	(1.65)	(2.23)	(3.36)	(3.49)	(1.43)	(1.16)	(3.30)	(3.57)	(1.57)	(2.97)
R^2	48	48	24	4	21	9	13	35	37	7	4	34	39	8	30
MAPE	0.26	0.26	0.33	0.37	0.34	0.36	0.35	0.30	0.29	0.36	0.37	0.31	0.29	0.36	0.31
N	138	138	138	138	138	138	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	0.76 ***	1.12 ***	1.03 ***	0.66 ***	0.73 ***	0.68 ***	0.70 ***	0.80 ***	0.83 ***	0.71 ***	0.66 ***	0.81 ***	0.79 ***	0.68 ***	0.84 ***
	(3.79)	(5.88)	(4.29)	(3.95)	(4.07)	(3.66)	(4.07)	(4.71)	(5.16)	(3.96)	(3.46)	(4.98)	(4.74)	(3.86)	(5.22)
Factor	-0.66 **	-2.19 ***	-0.43	-0.11	0.29 *	0.35	0.20	0.22 **	0.26 *	0.32	0.17	0.33 *	0.21 *	0.19	0.21 *
	(-2.25)	(-2.62)	(-1.36)	(-0.63)	(1.84)	(1.56)	(1.47)	(1.97)	(1.72)	(1.41)	(1.15)	(1.70)	(1.95)	(1.35)	(1.81)
R^2	20	25	10	2	15	8	11	18	16	8	4	16	19	8	17
MAPE	0.11	0.10	0.11	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table 3
War Factor versus Individual Traded Factors (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	1.16 ***	0.94 ***	1.48 ***	0.77 ***	0.92 ***	0.84 ***	0.88 ***	1.12 ***	1.12 ***	0.89 ***	0.81 ***	1.03 ***	1.08 ***	0.83 ***	1.08 ***
	(3.68)	(3.68)	(6.36)	(4.37)	(4.23)	(4.34)	(4.79)	(5.53)	(6.23)	(5.05)	(3.71)	(5.73)	(5.59)	(4.63)	(6.14)
Factor	-1.26 ***	-1.21 ***	-0.63 **	0.02	0.42 **	0.15	0.11	0.42 ***	0.33 *	0.18	0.03	0.32	0.32 **	0.05	0.18
	(-3.16)	(-3.10)	(-1.97)	(0.10)	(2.41)	(0.53)	(0.77)	(2.97)	(1.93)	(0.59)	(0.18)	(1.52)	(2.41)	(0.31)	(1.29)
R^2	22	21	12	-0	15	1	2	23	13	1	-0	9	18	0	7
MAPE	0.18	0.18	0.19	0.20	0.18	0.20	0.20	0.17	0.19	0.20	0.20	0.19	0.18	0.20	0.20
N	904	904	904	904	904	904	904	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	1.20	0.31	2.80 ***	0.50 ***	1.06 ***	0.56 ***	0.74 ***	1.51 ***	1.42 ***	0.73 ***	0.51 **	1.25 ***	1.38 ***	0.55 ***	1.18 ***
	(1.19)	(1.04)	(10.24)	(2.71)	(3.97)	(2.80)	(4.21)	(6.11)	(8.23)	(4.01)	(2.46)	(7.39)	(7.24)	(3.01)	(6.42)
Factor	-3.32 ***	-2.01 ***	-2.10 ***	-0.10	1.76 ***	0.41	0.29	1.32 ***	0.88 ***	0.50	0.24	0.92 ***	0.93 ***	0.14	0.41 ***
	(-3.42)	(-5.61)	(-5.25)	(-0.52)	(6.61)	(1.29)	(1.63)	(6.73)	(3.71)	(1.55)	(0.93)	(3.32)	(4.82)	(0.82)	(2.67)
R^2	62	38	24	0	22	2	3	28	15	3	0	13	21	1	9
MAPE	0.44	0.59	0.59	0.71	0.61	0.69	0.69	0.57	0.65	0.69	0.70	0.66	0.61	0.70	0.67
N	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Panel E: Own Constructed Anomalies

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	0.04	0.06 **	0.01	-0.01	0.04 *	-0.04	-0.01	0.07 **	0.04	-0.03	-0.05	0.01	0.06 **	-0.02	-0.01
	(0.83)	(2.11)	(0.16)	(-0.37)	(1.67)	(-1.18)	(-0.35)	(2.55)	(1.13)	(-0.81)	(-1.47)	(0.44)	(2.00)	(-0.49)	(-0.21)
Factor	-1.02 **	-2.29 ***	-0.36	-0.02	0.30 *	0.46 *	0.06	0.27 **	0.26	0.25	0.31 **	0.24	0.24 **	0.07	0.15
	(-2.12)	(-4.04)	(-1.06)	(-0.09)	(1.88)	(1.90)	(0.46)	(2.31)	(1.60)	(1.03)	(2.00)	(1.18)	(2.04)	(0.49)	(1.18)
R^2	19	20	3	-1	7	6	0	11	7	2	5	4	10	0	4
MAPE	0.32	0.34	0.36	0.40	0.35	0.37	0.39	0.33	0.34	0.38	0.38	0.36	0.33	0.39	0.36
N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Panel F: Own Constructed Nonlinear Portfolios

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	1.18 ***	0.95 ***	1.72 ***	1.25 ***	1.09 ***	1.23 ***	1.16 ***	1.27 ***	1.31 ***	1.39 ***	1.15 ***	1.27 ***	1.25 ***	1.19 ***	1.41 ***
	(3.60)	(3.58)	(6.00)	(6.37)	(5.17)	(6.47)	(6.23)	(6.63)	(7.09)	(7.18)	(5.40)	(6.88)	(6.65)	(6.44)	(7.03)
Factor	-0.89 ***	-0.26	-0.73 *	-0.28	0.54 **	0.81 **	0.25	0.44 **	0.38 **	0.80 **	0.45 **	0.43 *	0.36 **	0.28	0.29 *
	(-3.64)	(-0.57)	(-1.96)	(-1.29)	(2.10)	(2.23)	(1.59)	(2.47)	(2.01)	(1.99)	(2.26)	(1.87)	(2.22)	(1.51)	(1.87)
R^2	16	1	27	13	29	19	20	36	30	25	7	27	33	18	28
MAPE	0.10	0.10	0.09	0.10	0.09	0.09	0.09	0.08	0.09	0.09	0.10	0.09	0.08	0.09	0.09
N	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table 4
Cross-Sectional Tests: ***War*** versus NVIX_War^2 and GPR

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premia. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. *WarFac* is the innovation in *War*. *NVIX_War2Fac* is the innovation in NVIX_War^2 from Manela and Moreira (2017), and *GPRFac* is the innovation in geopolitical risk (GPR) from Caldara and Iacoviello (2022). Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to March 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)
Intercept	0.20 ***	0.25 ***	0.20 ***	0.12 ***
	(3.24)	(5.06)	(6.57)	(2.76)
WarFac	-1.31 ***			-1.04 **
	(-2.88)			(-2.36)
NVIX_War2Fac		-0.65		0.10
		(-1.63)		(0.28)
GPRFac			0.44	0.20
			(1.36)	(0.53)
R^2	46	3	2	56
MAPE	0.27	0.38	0.38	0.24
N	138	138	138	138
T	522	522	522	522

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)
Intercept	0.76 ***	0.60 ***	0.64 ***	0.87 ***
	(3.67)	(3.03)	(3.17)	(4.23)
WarFac	-0.67 **			-0.60 **
	(-2.29)			(-2.22)
NVIX_War2Fac		-0.07		0.09
		(-0.45)		(0.61)
GPRFac			0.16	0.02
			(1.28)	(0.11)
R^2	20	0	1	25
MAPE	0.11	0.12	0.12	0.11
N	1372	1372	1372	1372
T	522	522	522	522

Table 4
Cross-Sectional Tests: *War* versus NVIX^2 and GPR (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)
Intercept	1.12 ***	0.75 ***	0.89 ***	1.31 ***
	(3.55)	(2.92)	(4.10)	(4.83)
WarFac	-1.24 ***			-1.03 ***
	(-3.06)			(-2.80)
NVIX_War2Fac		0.39 ***		0.59 ***
		(2.94)		(2.81)
GPRFac			0.51	0.12
			(1.22)	(0.23)
R^2	22	1	3	30
MAPE	0.18	0.20	0.19	0.17
N	904	904	904	904
T	522	522	522	522

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)
Intercept	1.18	0.28	0.84 ***	1.77 ***
	(1.12)	(0.50)	(2.64)	(3.28)
WarFac	-3.47 ***			-2.76 *
	(-3.34)			(-1.89)
NVIX_War2Fac		-1.68 ***		0.07
		(-3.42)		(0.10)
GPRFac			1.44	-0.07
			(1.36)	(-0.04)
R^2	59	5	5	65
MAPE	0.47	0.70	0.68	0.44
N	360	360	360	360
T	522	522	522	522

Table 5
Cross-Sectional Tests: *War* versus Crisis Events

Every month, we run the following cross-sectional regression:

$$R^e_{i\tau} = \lambda_{0t} + \lambda_t \beta_{it-1} + \lambda_t^{MKT} \beta_{it-1}^{MKT} + \lambda_t^{SMB} \beta_{it-1}^{SMB} + \lambda_t^{HML} \beta_{it-1}^{HML} + e_{it},$$

where R^e_{it} is the excess return portfolio i in month t, β_{t-1} is the vector of portfolio betas concerning our *War* factor (WarFac), a crisis count factor (CrisisFac), and a war count factor (CWarFac) studied in Berkman, Jacobsen, and Lee (2011), market factor (MKT), value factor (HML), and size factor (SMB) computed over a rolling 60-month window. λ_t is the vector of return premia in month t. Reported are the time series averages of return premia λ with t-statistics computed using Newey and West (1987) standard errors. The last row reports the time series average of the cross-sectional R^2s. Both return premia and R^2s are in percentage points. Panel A (B) reports the Fama-French 30 (49) industry portfolio results. The sample period is from July 1926 to December 2018. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: 30 Industry Portfolios

	(1)	(2)	(3)	(4)
Intercept	0.82 ***	0.89 ***	0.74 ***	0.77 ***
	(4.83)	(5.22)	(4.19)	(4.43)
WarFac	-0.24 *			-0.32 **
	(-1.89)			(-2.39)
CrisisFac		-0.35 ***		-0.30 **
		(-3.06)		(-2.27)
CWarFac			-0.26 **	-0.23 *
			(-2.31)	(-1.94)
MKT	-0.04	-0.09	0.13	0.10
	(-0.20)	(-0.48)	(0.59)	(0.50)
SMB	0.13	0.10	0.08	0.11
	(1.19)	(0.87)	(0.71)	(0.98)
HML	0.19	0.19	0.14	0.17
	(1.57)	(1.59)	(1.11)	(1.30)
R^2	21	20	19	22

Table 5
Cross-Sectional Tests: *War* versus Crisis Events (Cont.)

Panel B: 49 Industry Portfolios

	(1)	(2)	(3)	(4)
Intercept	0.70 ***	0.76 ***	0.73 ***	0.68 ***
	(4.53)	(4.99)	(4.63)	(4.48)
WarFac	-0.19			-0.28 **
	(-1.53)			(-2.16)
CrisisFac		-0.24 **		-0.23 **
		(-2.46)		(-2.04)
CWarFac			-0.09	-0.20 *
			(-0.80)	(-1.72)
MKT	0.09	0.04	0.14	0.17
	(0.52)	(0.24)	(0.73)	(0.89)
SMB	0.12	0.09	0.10	0.11
	(1.22)	(0.95)	(0.92)	(1.10)
HML	0.27 **	0.23 **	0.22 **	0.27 **
	(2.49)	(2.20)	(2.02)	(2.33)
R^2	17	17	16	19

Internet Appendix
War Discourse and
the Cross Section of Expected Stock Returns

A Method, Estimation, and Data

This appendix discusses the semisupervised topic model and our estimation scheme in more detail. Table A.1 reports the full list of seed words as input into our topic model and Figure A.1 plots the monthly count and length of *NYT* articles in our sample.

A.1 Seeded Latent Dirichlet Distribution

This appendix provides more details on the seeded latent Dirichlet distribution model. This paper uses a stochastic topic model to extract latent topic weights from news articles. Topic models are developed based on the core idea that documents are mixtures of topics, where each topic has a probability distribution over words (Blei 2012; Steyvers and Griffiths 2007). Under topic models, we assume that text documents derive from a stochastic generative process. The creation of a new document starts with a document-specific distribution over topics (the document-topic distribution). Each word in the document is chosen first by picking a topic randomly from the document-topic distribution and then drawing a word from the topic-word distribution for that topic. To model this, every possible word must be assigned to a topic.

In this setup, the document-topic distribution for each document and topic-word distribution for each topic (the same across documents) are unobserved parameters that are estimated from the observable word frequencies in the document collection. In other words, we can use standard statistical techniques to estimate the generative process, inferring the topics responsible for generating a collection of documents (Steyvers and Griffiths 2007).

The most widely used topic model is latent Dirichlet allocation (LDA) as introduced by Blei, Ng, and Jordan (2003) and further developed by Griffiths and Steyvers (2004). Under LDA, a document d is generated under the following hierarchical process:

- The word weight vector ω_k of topic k is the vector of probabilities of each word value for the topic k. The prior for these weights is assumed to have a Dirichlet distribution governed by parameter β: $\omega_k \sim \text{Dirichlet}(\beta)$.[1]
- The topic weight in a document d, denoted τ_d, is a vector of topic probabilities, i.e., probabilities that any given word location in the document is about any given topic.

[1] To illustrate, suppose that topic k has three words: $word_1$, $word_2$, and $word_3$ with weights $\omega_k = [w_1, w_2, w_3]$ with $w_1 + w_2 + w_3 = 1$. The model assumes that this ω_k vector follows a Dirichlet distribution.

The topic weight vector of document d follows a prior Dirichlet distribution governed by parameter α, the same for all documents: $\tau_d \sim \text{Dirichlet}(\alpha)$, the same for all documents.[2]

- We use v to indicate a word location in a given document and w to indicate a word value (such as "the" or "cat"). For each word location v in document d, we
  - randomly select a topic from the document-topic distribution:
    $z_{dv} \sim \text{Multinomial}(\tau_d)$ (a distribution which does not depend on v), and then
  - randomly select a word from that topic:
    $w \sim \text{Multinomial}(\omega_{z_{dv}})$.

In other words, it is the multinomial distribution of word values for the realized topic z_{dv}.

In this setup, the topic-word distribution ω_k and document-topic distribution τ_d are latent parameters that we want to estimate. Estimating these involves a backward inference based on observed word frequencies across documents. The parameters α and β are hyperparameters of the prior distribution whose values are taken from the Latent Dirichlet Distribution topic modeling literature.

The document-topic distribution τ_d is of utmost interest because it summarizes the attention allocated to each topic in each news article. To estimate these parameters using a Bayesian method, Griffiths and Steyvers (2004) specifies that ω_k and τ_d follow two Dirichlet distributions (these two are referred to as the "prior" distribution in Bayesian statistic). From these specifications, we can derive the distribution of the topic assignment z_{dv} conditioned on observed word frequencies (this conditional distribution is referred to as the "posterior" distribution). We then use Gibbs sampling to simulate this posterior distribution and estimate the two hidden model parameters.[3]

Users of the traditional unsupervised LDA developed by Blei, Ng, and Jordan (2003) and Griffiths and Steyvers (2004) only need to prespecify the number of topics K and let the model cluster words into these topics based on word frequencies in a completely unsupervised manner. Specifically, the LDA model is more likely to assign a word w to a topic k in a document d if w has been assigned to k across many different documents and k has been

[2] Similarly, assume document d has four topics $topic_1$, $topic_2$, $topic_3$, $topic_4$ with the weights given to these topics captured by $\tau_d = [\theta_1, \theta_2, \theta_3, \theta_4]$ with $\theta_1 + \theta_2 + \theta_3 + \theta_4 = 1$. The model assumes that this τ_d vector follows a Dirichlet distribution.

[3] Gibbs sampling is a sampling technique to simulate a high-dimensional distribution by sampling from lower-dimensional subsets of variables where each subset is conditioned on the value of all others. See Griffiths and Steyvers (2004) for details on the implementation of Gibbs sampling in LDA.

used multiple times in d (Steyvers and Griffiths 2007). The model automatically extracts underlying topics, so users of LDA have no control over topic assignments.

Since we are interested in uncovering specific topics, we employ a recent extension of LDA called seeded LDA (sLDA) developed by Lu et al. (2011). sLDA allows users to regulate topic contents using domain knowledge by injecting seed words (prior knowledge) into the model. Precisely, under sLDA, we specify the topic-word distribution as follows:

$$\omega_k \sim \text{Dirichlet}\left(\beta + C_w\right)_{w \in V}, \tag{A.1}$$

where V is the corpus or text collection, $C_w > 0$ when w is a seed word in topic k and $C_w = 0$ when w is not a seed word. The higher is C_w, the stronger the tilt toward word w appearing in any given topic. Intuitively, sLDA gives preference to seed words w in topic k in the form of pseudo count C_w and clusters words into topics based on their co-occurrences with the seed words. When a seed word is not present in a text collection, it does not enter the sLDA model and has no impact on the estimation process.

Estimation is implemented by the seededlda package in R and run on a high-performance computing (HPC) cluster. Full estimation of the model parallelized on 80 computational nodes requires about one week to complete. Following standard practice, we set $\alpha = 50/K$ where K is the number of topics, $\beta = 0.1$, and $C_w = 0.01$ times the number of terms in the corpus.

A.2 Estimation

We use Gibbs sampling to estimate the model's parameters during each monthly estimation. We draw 200 drawings from the posterior distribution of z_{dv}, the realized topic for word location v in document d in the sLDA model, where we are conditioning on observed word frequencies.[4] In each drawing, we condition on the estimated values of the parameters of the model derived from previous drawing (where in the first draw, the initial estimate comes from a random number generator). In the last draw, we estimate our final value of the document-topic weights τ_d; that is, we estimate one 14×1 vector $\tau_d = [\tau_d^1, \tau_d^2, \ldots, \tau_d^{14}]$ for each news article, d, in the estimation window.

We then provide estimates of model parameters that condition on month t within the

[4]In addition to the number of topics and articles, the number of samples drawn from the posterior distribution is a computational cost consideration in any topic model.

dataset. We compute the global monthly weights of each topic k ($k = 1, 2, \ldots, 14$) as the average weight of each topic across all articles in month t, weighted by the length $L(d)$ of each article:

$$\tau_t^k = \frac{\sum_{d=1}^{n_t} \tau_d^k L(d)}{\sum_{d=1}^{n_t} L(d)}, \tag{A.2}$$

where τ_t^k is the weight of topic k in month t, n_t is the total number of news articles in month t, and $L(d)$ is the total number of unigrams (one-word terms), bigrams (two-word terms), and trigrams (three-word terms) in article d.[5] (Equal weighting of topic weights across articles yields similar results.)

[5] An n-gram is a sequence of n words. For instance, "San Diego" is a bigram, and "A study of topics is needed" is a 6-gram.

Figure A.1. ***NYT*** **Article Count and Length**

This figure plots the time series of the monthly total count and the monthly average length of articles in the *NYT*. Article length is measured as the sum of unigrams (one-word terms), bigrams (two-word terms), and trigrams (three-word terms) of each article. The sample period is from January 1871 to October 2019. Articles with limited content have been removed.

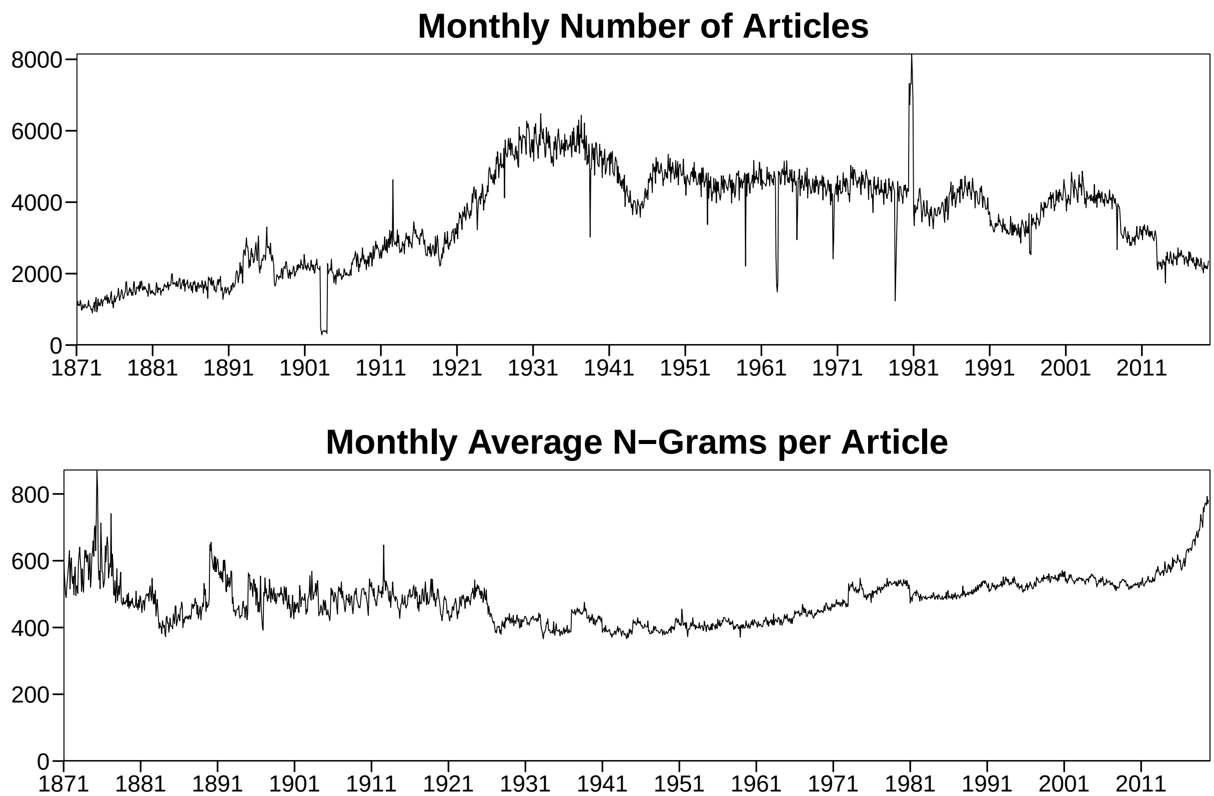


Table A.1
Seed Words

This table lists the *lemmatized* seed words for each of the 14 discourse topics. The first column presents the full name of the topic, and the second column reports the short name used in the paper.

Narrative	Short Name	Seed Words
War	War	war
Pandemic	Pandemic	epidemic, pandemic
Panic	Panic	bank failure, bank panic, bank run, crisis, depression, downturn, fear, financial panic, hard time, panic, recession
Confidence	Confidence	business confidence, consumer confidence
Frugality	Saving	compassion, family morale, frugal, frugality, modesty, moral, poverty, saving
Conspicuous Consumption	Consumption	american dream, conspicuous consumption, consumption, equal opportunity, equality, homeownership, luxury, patriotism, prosperity
Monetary Standard	Money	bimetallism, devaluation, gold, gold standard, inflation, monetary standard, money, silver
Techmology Replacing Jobs	Tech	automate, computer, digital divide, electronic brain, invention, labor save, labor save machine, machine, mechanize, network, technocracy, technological unemployment, technology, unemployment
Real Estate Booms	Real_estate_boom	boom, bubble, flip, flipper, home ownership, home purchase, house boom, house bubble, land boom, land bubble, price increase, real estate boom, real estate bubble, speculation
Real Estate Bursts	Real_estate_bust	bust, crash, house bust, house crash, land bust, land crash, price decrease, real estate bust, real estate crash
Stock Market Bubbles	Stock_bubble	advance market, boom, bubble, bull, bull market, bullish, earnings per share, inflate market, margin, margin requirement, market boom, market bubble, price earn ratio, price increase, sell short, short sell, speculation, stock market boom, stock market bubble
Stock Market Crashes	Stock_crash	bear, bear market, bearish, bust, crash, fall market, market crash, stock crash, stock market crash, stock market decline
Boycotts and Evil Business	Boycott	anger, boycott, community, evil business, excess profit, fair wage, moral, outrage, postpone purchase, profiteer, protest, strike, wage cut
Wage and Labor Unions	Wage	consumer price, cost of live, cost push, cost push inflation, high wage, increase wage, inflation, labor union, rise cost, wage, wage demand, wage lag, wage price, wage price spiral

B Additional Results with Our Test Portfolios

This subsection presents additional two-pass test results with our own constructed portfolios in Table B.1 and Table C.2. We discuss these results in the main text.

Table B.1
War Factor and Return Premium

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include 128 own constructed anomalies in Panel A and 1173 own constructed nonlinear portfolios in Panel B. "WarFac" is the innovation *War* derived from rolling estimation of an AR(1) process; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD" and "FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_MKT, R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.04	0.02	0.04	-0.02	0.00	0.04	-0.00	0.04	0.00	0.00	-0.01
	(0.83)	(1.08)	(1.58)	(-0.79)	(0.03)	(0.62)	(-0.07)	(1.04)	(0.00)	(0.08)	(-0.29)
WarFac	-1.02 **					-1.47 ***	-1.76 ***	-1.53 ***	-1.34 ***	-1.00 ***	-1.16 ***
	(-2.12)					(-5.23)	(-5.11)	(-4.66)	(-4.78)	(-4.16)	(-4.07)
MKT		0.09	0.41	0.82 **		0.17	-0.23	-0.16	0.57		0.13
		(0.33)	(1.48)	(2.51)		(0.33)	(-0.57)	(-0.41)	(1.25)		(0.34)
SMB		0.24	0.34 **				0.16	0.17			0.13
		(1.57)	(2.00)				(0.82)	(0.80)			(0.66)
HML		0.33 **					0.44 **				0.43 **
		(2.16)					(2.19)				(2.25)
RMW		0.09					0.13				0.00
		(0.74)					(0.81)				(0.02)
CMA		0.26 ***					0.34 **				0.27 **
		(2.62)					(2.49)				(2.01)
MOM		0.74 ***					0.82 ***				0.41 *
		(3.50)					(3.10)				(1.68)
MGMT			0.50 ***					0.55 ***			0.56 ***
			(3.26)					(2.86)			(2.90)
PERF			0.63 ***					0.60 **			0.18
			(2.86)					(2.07)			(0.61)
PEAD				0.47 ***					0.36		0.87 ***
				(2.91)					(1.54)		(3.13)
FIN				0.42 **					0.47 *		1.18 ***
				(2.08)					(1.94)		(4.17)
R_MKT					0.50					0.16	
					(1.59)					(0.47)	
R_ME					0.51 ***					0.54 **	0.65 ***
					(2.59)					(2.57)	(3.18)
R_IA					0.33 ***					0.31 **	0.43 ***
					(2.70)					(2.38)	(3.06)
R_ROE					0.15					0.22	0.34 **
					(0.97)					(1.44)	(2.08)
R_EG					1.26 ***					0.94 ***	1.13 ***
					(7.43)					(5.19)	(6.59)
R^2	19	23	30	14	47	22	43	44	26	50	53
MAPE	0.32	0.29	0.28	0.33	0.25	0.33	0.27	0.27	0.31	0.25	0.25
N	128	128	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532	532	532

Table B.1
War Factor and Return Premium (Cont.)

Panel B: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	1.18 ***	0.96 ***	1.03 ***	1.37 ***	1.02 ***	1.79 ***	0.85 ***	1.01 ***	0.95 ***	0.98 ***	0.60 ***
	(3.60)	(4.72)	(5.07)	(5.28)	(4.71)	(5.57)	(3.42)	(4.12)	(3.06)	(3.85)	(2.69)
WarFac	-0.89 ***					-0.66 **	-0.87 ***	-0.73 ***	-1.03 ***	-0.82 ***	-0.70 ***
	(-3.64)					(-2.22)	(-6.03)	(-4.05)	(-4.46)	(-5.35)	(-6.46)
MKT		-0.29	-0.32	-0.29		-0.77 *	-0.05	-0.09	0.23		0.20
		(-0.96)	(-1.04)	(-0.94)		(-1.88)	(-0.16)	(-0.28)	(0.68)		(0.66)
SMB		0.32 *	0.32				0.05	-0.05			0.02
		(1.84)	(1.61)				(0.25)	(-0.28)			(0.12)
HML		0.15					0.18				0.30
		(0.91)					(0.98)				(1.63)
RMW		0.23					0.50 ***				0.41 ***
		(1.46)					(3.03)				(2.81)
CMA		0.57 ***					0.49 ***				0.52 ***
		(4.98)					(3.87)				(4.35)
MOM		0.53 **					0.71 ***				0.73 ***
		(2.33)					(3.02)				(3.15)
MGMT			0.48 ***					0.60 ***			0.43 **
			(2.90)					(3.51)			(2.33)
PERF			0.58 **					0.74 ***			1.37 ***
			(2.36)					(2.71)			(5.05)
PEAD				0.29 *					0.40 *		0.20
				(1.70)					(1.74)		(1.14)
FIN				0.38					0.89 ***		1.27 ***
				(1.52)					(3.36)		(5.38)
R_MKT					-0.26					-0.11	
					(-0.87)					(-0.33)	
R_ME					0.29 *					0.16	0.01
					(1.72)					(0.93)	(0.07)
R_IA					0.33 **					0.36 **	0.32 **
					(2.51)					(2.45)	(2.55)
R_ROE					0.24					0.51 ***	0.51 ***
					(1.27)					(2.59)	(2.90)
R_EG					0.88 ***					0.82 ***	0.79 ***
					(4.48)					(3.70)	(5.00)
R^2	16	48	46	30	48	35	55	53	46	54	62
MAPE	0.10	0.07	0.07	0.09	0.07	0.08	0.07	0.07	0.08	0.07	0.06
N	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532	532	532

C Construction of WarFac Mimicking Portfolio

We construct factor mimicking portfolios and re-perform tests to tackle the inflation estimation issue of non-traded factors return premium. The FMP represents a linear projection of the non-traded asset on the return space and carries the same pricing information as the original factor (Cochrane 2005, Chapter 6).

To construct a mimicking portfolio of WarFac (WMP), first, we apply the cross-sectional approach proposed by Lehmann and Modest (1988) and applied by several papers, including Cooper and Priestley (2011). Essentially, this approach uses the prices of risk from the second-pass cross-sectional regression as a mimicking portfolio. Specifically, the slope in the monthly cross-sectional regression of asset returns onto WarFac betas is used as the monthly mimicking portfolio where the WarFac betas are estimated once using the whole sample. The key component of this approach is testing assets, which we rely on the tree-based portfolios from Bryzgalova, Pelger, and Zhu (2023) as the authors claim that these assets span the universe of testing assets more than the other characteristics-sorted portfolios.

We will show next that the WMP generates a good spanning test, significant prices of risk, and passes the protocol and the three-pass test. We thus adhere to this approach and present it as our main result of WMP. Pukthuanthong et al. (2022) also show the cross-sectional approach outperforms the other approaches of mimicking portfolios construction.

To confirm the robustness of our result, we also construct the WMP using the time series approach (see Adrian, Etula, and Muir (2014)) by projecting our nontraded WarFac onto the space of excess returns:

$$WarFac_t = \alpha + \beta' R^e + \epsilon_t, \tag{C.1}$$

where R^e is the vector of excess returns on 360 tree-based portfolios. Besides the tree-based portfolios, another set of basis assets we use includes 30 portfolios comprising ten equal-weighted portfolios sorted on the market value of equity, ten equal-weighted portfolios sorted on book-market ratio, and ten value-weighted portfolios sorted on past 12-month returns (i.e., momentum) downloaded from Ken French's website.[6] We follow Cooper and Priestley (2011) and Pukthuanthong, Roll, and Subrahmanyam (2019) in using the equal-weighted returns on the size and book-market portfolios because equal-weighted returns on

[6] Ideally, the error ϵ_t is orthogonal to the space of returns so that the covariance of any asset with WarFac is identical to its covariance with the mimicking portfolio, defined as the fitted value of the regression.

these characteristics have more variation and span a larger portion of the return space than do the value-weighted ones. Using these portfolios also enables us to use a long time series from 1926 to 2019 to construct a portfolio that mimics Warfac since data on these portfolios are available from 1926.

We then define the WMP in the time-series approach as the fitted value

$$WMP_t = \hat{\beta}' R_t^e, \tag{C.2}$$

where $\hat{\beta}$ is estimated via OLS from 1926 to 2019.

From this point onward, we focus the WMP result using a cross-sectional approach. Panel A of Table C.1 reports the summary statistics of WMP and other traded factors over 1972-2016. WMP has a monthly average return of -3.32%, consistent with the negative return premium estimate for WarFac, and a monthly standard deviation of return of 6.64%, yielding an absolute annualized Sharpe ratio of 1.73, highest compared those of the remaining factors. R_EG and PEAD have the second and third-highest Sharpe ratios (1.53 and 1.16, respectively).

C.1 Spanning Tests

We first examine whether WMP expands the efficient frontier by running spanning tests of WMP on benchmark factor models. Specifically, we run the following time series regression:

$$WMP_t = \alpha + \beta' F_t + \epsilon_t, \tag{C.3}$$

where F_t is the vector of traded factors. As reported in Panel C of Table C.1, WMP has a monthly alpha of around 3.10%, significant at the 1% level, when tested against each or all factor models together. This result indicates that WMP can be combined with the corresponding benchmark factors to generate a portfolio which mean-variance dominates the benchmark factors (Back 2018, page 143). Furthermore, all factors combined explain only 19% of the time-series variation of WMP.

Panel B examines the regression of other factors on WMP. We find WMP subsumes SMB, HML, CMA of FF6, MGMT of M4, FIN of DHS, and R_IA of Q5 as indicated by the insignificance of their alphas. For RMW, the alpha is weakly significant at 10% level.

C.2 Pricing Results: WMP versus Factor Models

To test the performance of *War* in explaining the cross section of expected returns, we investigate the pricing performance of the WarFac mimicking portfolio (WMP) using the same test assets we use with WarFac. We report the results for 138 long-short anomaly portfolios from HXZ, 1372 single-sorted portfolios from HXZ, 904 single-sorted portfolios from CZ, and 360 ML-based nonlinear portfolios in Table C.2. The results for our 128 own-constructed anomaly portfolios and our 2,190 own-constructed nonlinear portfolios are reported in Table C.2.

In a single-factor model with WMP, the return premium for loadings on war risk is negative across test assets, all significant at the 1% level except for our own constructed nonlinear portfolios. The monthly return premium for loadings on WMP is -3.12% for the 138 anomaly characteristic portfolios from HXZ, -2.19% for the 1,372 single-sorted portfolios from HXZ, -1.21% for the 904 single-sorted portfolios from CZ, -2.01% for the 360 ML-based nonlinear portfolios, -2.29% for our own-constructed 128 anomaly characteristic portfolios, and -0.26% for our 2,019 own-constructed nonlinear portfolios. Hence, the absolute return premium for loadings on war risk is, on average, 1.84% per month (or 22.16% per annum) across test assets. The return premia of WMP remains significant at least the 5% level in all other specifications across all test asset sets. As a solo-factor model, the average R^2 for WMP across six sets of test assets is 25.5%. Our result remains robust using our own constructed long-short and nonlinear portfolios.

These results indicate that the pricing power of WMP constructed using a cross-sectional approach aligns closely with that of the WarFac generated from a shock in the first-order autoregressive process.

The WMP constructed by the time-series approach using tree-based and 30 characteristics-sorted portfolios also generates significant and negative return premiums across most of testing assets. See Table E.2 in Appendix E for the results.

Table C.1
War Mimicking Portfolio: Summary Statistic and Spanning Tests

Panel A of this table reports the mean, standard deviation (SD), and annualized Sharpe ratio (SR) of monthly returns on our *War* mimicking portfolio (WMP) and traded factors consisting of "MKT, SMB, HML, RMW, CMA, MOM" from Fama and French (2018); "MGMT, PERF" from Stambaugh and Yuan (2017); "PEAD, FIN" from Daniel, Hirshleifer, and Sun (2020); and "R_ME, R_IA, R_ROE, R_EG" from Hou et al. (2021). Panel B reports the time-series regressions of each traded factors onto WMP

$$F_t = \alpha + \beta^W MP_t + \epsilon_t.$$

And Panel C reports the time-series regression of WMP onto traded factors

$$WMP_t = \alpha + \beta^{'} F_t + \epsilon_t,$$

where F_t is the vector of traded factors. Alpha and R^2 are in percent, and t-statistics are computed with Newey and West (1987) standard errors. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary Statistics

	WMP	MKT	SMB	HML	RMW	CMA	MOM	MGMT	PERF	PEAD	FIN	R_ME	R_IA	R_ROE	R_EG
Mean	-3.32	0.56	0.18	0.40	0.28	0.35	0.68	0.65	0.64	0.63	0.80	0.30	0.41	0.55	0.83
SD	6.64	4.53	3.08	2.93	2.34	1.95	4.42	2.81	3.92	1.88	3.89	3.06	1.86	2.58	1.88
SR	-1.73	0.43	0.20	0.47	0.42	0.62	0.53	0.80	0.57	1.16	0.71	0.33	0.76	0.73	1.53

Panel B: WMP Spans Other Factors

	MKT	SMB	HML	RMW	CMA	MOM	MGMT	PERF	PEAD	FIN	R_ME	R_IA	R_ROE	R_EG
α	1.36 ***	0.19	0.03	0.21 *	0.05	0.62 **	0.23	0.52 **	0.61 ***	0.24	0.30 **	0.14	0.62 ***	0.63 ***
	(6.82)	(1.24)	(0.18)	(1.85)	(0.43)	(2.25)	(1.61)	(2.32)	(5.85)	(1.20)	(1.98)	(1.36)	(3.82)	(6.23)
β	0.24 ***	0.00	-0.11 ***	-0.02	-0.09 ***	-0.02	-0.12 ***	-0.04	-0.01	-0.17 ***	0.00	-0.08 ***	0.02	-0.06 ***
	(6.61)	(0.15)	(-3.57)	(-0.99)	(-4.93)	(-0.33)	(-4.47)	(-0.84)	(-0.37)	(-4.47)	(0.07)	(-4.32)	(0.71)	(-3.14)
R^2	12	-0	6	0	9	-0	9	0	-0	8	-0	8	0	4

Table C.1

***War* Mimicking Portfolio: Summary Statistic and Spanning Test (Cont.)**

Panel C: Other Factors Span WMP

	(1)	(2)	(3)	(4)	(5)
α	-3.27 ***	-3.20 ***	-3.37 ***	-3.11 ***	-3.01 ***
	(-8.84)	(-8.44)	(-8.43)	(-7.52)	(-7.76)
MKT	0.44 ***	0.42 ***	0.41 ***		0.36 ***
	(4.87)	(3.91)	(4.46)		(4.02)
SMB	-0.23	-0.30 *			-0.94 *
	(-1.37)	(-1.83)			(-1.94)
HML	-0.21				-0.39
	(-0.94)				(-1.50)
RMW	-0.03				-0.01
	(-0.16)				(-0.03)
CMA	-0.48 *				-0.20
	(-1.70)				(-0.41)
MOM	0.00				0.01
	(0.03)				(0.05)
MGMT		-0.47 **			0.36
		(-2.11)			(1.31)
PERF		0.01			-0.17
		(0.07)			(-0.95)
PEAD			0.01		-0.00
			(0.07)		(-0.02)
FIN			-0.24 **		-0.27
			(-2.00)		(-1.24)
R_MKT				0.42 ***	
				(5.12)	
R_ME				-0.16	0.71 *
				(-1.14)	(1.67)
R_IA				-0.50 *	-0.23
				(-1.91)	(-0.48)
R_ROE				0.48 **	0.54 **
				(2.26)	(2.44)
R_EG				-0.56 ***	-0.53 **
				(-3.07)	(-2.44)
R^2	16	15	14	18	19

Table C.2
War Mimicking Portfolio and Return Premium

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. "WMP" is the mimicking portfolio of WarFac; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD, FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_MKT, R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: long-short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.23 ***	0.16 ***	0.15 ***	0.09 ***	0.10 ***	0.22 ***	0.16 ***	0.13 ***	0.10 ***	0.09 ***	0.06 ***
	(5.33)	(7.08)	(4.81)	(3.23)	(3.00)	(5.88)	(6.16)	(4.00)	(3.56)	(2.76)	(2.85)
WMP	-3.12 ***					-2.97 ***	-3.42 ***	-2.75 ***	-2.82 ***	-2.17 ***	-3.01 ***
	(-3.92)					(-3.27)	(-5.51)	(-4.16)	(-3.23)	(-2.88)	(-4.65)
MKT		0.48	0.89 **	1.14 ***		-0.83 **	0.48	0.66 *	0.54		0.60 *
		(1.50)	(2.51)	(2.98)		(-2.52)	(1.41)	(1.87)	(1.54)		(1.78)
SMB		0.05	-0.02				-0.17	-0.13			0.01
		(0.30)	(-0.15)				(-1.02)	(-0.73)			(0.06)
HML		0.27					0.27				0.59 ***
		(1.60)					(1.53)				(3.36)
RMW		0.28 **					0.20				0.15
		(2.27)					(1.57)				(1.15)
CMA		0.54 ***					0.49 ***				0.20 *
		(4.91)					(4.28)				(1.70)
MOM		0.61 ***					0.56 ***				0.35
		(2.91)					(2.64)				(1.64)
MGMT			0.71 ***					0.56 ***			0.59 ***
			(4.50)					(3.48)			(3.29)
PERF			0.47 *					0.55 **			-0.01
			(1.93)					(2.27)			(-0.03)
PEAD				0.36 **					0.49 ***		0.49 ***
				(2.19)					(2.98)		(3.46)
FIN				0.96 ***					0.83 ***		0.69 ***
				(4.64)					(4.10)		(3.01)
R_MKT					0.66 *					0.60 *	
					(1.87)					(1.71)	
R_ME					0.25					0.12	0.05
					(1.48)					(0.63)	(0.28)
R_IA					0.44 ***					0.40 ***	0.43 ***
					(3.66)					(3.36)	(3.52)
R_ROE					0.33 **					0.30 **	0.43 ***
					(2.40)					(2.14)	(3.18)
R_EG					0.80 ***					0.75 ***	0.79 ***
					(6.05)					(5.42)	(6.44)
R^2	48	59	65	51	77	48	70	71	69	80	85
MAPE	0.26	0.21	0.20	0.24	0.15	0.26	0.18	0.19	0.19	0.14	0.12
N	138	138	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532	532	532

Table C.2
War Mimicking Portfolio and Return Premium (Cont.)

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	1.12 ***	0.43 **	0.25	-0.22	0.35	1.07 ***	0.46 **	0.35	0.04	0.39 *	0.31
	(5.88)	(2.12)	(1.11)	(-0.81)	(1.55)	(4.20)	(2.15)	(1.52)	(0.15)	(1.71)	(1.44)
WMP	-2.19 ***					-2.38 ***	-1.86 ***	-1.78 ***	-2.15 ***	-1.61 ***	-1.62 ***
	(-2.62)					(-3.29)	(-4.18)	(-4.00)	(-3.48)	(-3.55)	(-3.77)
MKT		0.16	0.34	0.84 **		-0.48	0.13	0.23	0.57 *		0.29
		(0.55)	(1.08)	(2.47)		(-1.49)	(0.44)	(0.71)	(1.67)		(0.99)
SMB		0.16	0.20				0.11	0.16			0.14
		(1.08)	(1.31)				(0.79)	(1.02)			(0.97)
HML		0.30 **					0.33 **				0.50 ***
		(1.98)					(2.12)				(3.32)
RMW		0.18					0.19				0.11
		(1.56)					(1.61)				(0.99)
CMA		0.20 **					0.23 **				0.20 **
		(2.06)					(2.36)				(2.03)
MOM		0.58 ***					0.58 ***				0.39 *
		(2.84)					(2.83)				(1.93)
MGMT			0.46 ***					0.43 ***			0.33 **
			(2.89)					(2.71)			(2.23)
PERF			0.47 **					0.52 **			0.31
			(2.12)					(2.35)			(1.46)
PEAD				0.32 **					0.41 ***		0.36 ***
				(2.13)					(2.73)		(3.15)
FIN				0.57 ***					0.66 ***		0.48 **
				(2.84)					(3.24)		(2.42)
R_MKT					0.24					0.20	
					(0.77)					(0.63)	
R_ME					0.34 **					0.30 **	0.23
					(2.29)					(2.01)	(1.61)
R_IA					0.27 **					0.28 **	0.29 ***
					(2.43)					(2.45)	(2.98)
R_ROE					0.23 *					0.23 *	0.37 ***
					(1.76)					(1.75)	(2.94)
R_EG					0.61 ***					0.58 ***	0.63 ***
					(5.65)					(5.30)	(6.38)
R^2	25	42	43	34	55	25	48	48	48	58	65
MAPE	0.10	0.09	0.09	0.09	0.08	0.10	0.08	0.08	0.08	0.08	0.07
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532	532	532

Table C.2
War Mimicking Portfolio and Return Premium (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.94 ***	0.93 ***	0.76 ***	1.59 ***	0.65 ***	1.46 ***	0.65 ***	0.34 **	0.33 **	0.40 **	0.33
	(3.68)	(5.93)	(4.76)	(7.04)	(3.28)	(6.13)	(4.47)	(2.33)	(2.12)	(2.25)	(1.58)
WMP	-1.21 ***					-1.33 ***	-1.46 ***	-1.55 ***	-2.10 ***	-1.64 ***	-1.81 ***
	(-3.10)					(-3.64)	(-4.54)	(-4.84)	(-5.75)	(-4.84)	(-5.19)
MKT		-0.40	-0.24	-0.77 ***		-0.75 **	-0.06	0.26	0.44 *		0.30
		(-1.56)	(-0.91)	(-2.69)		(-2.46)	(-0.25)	(1.03)	(1.68)		(1.03)
SMB		0.35 **	0.47 ***				0.18	0.22			0.09
		(2.32)	(3.00)				(1.29)	(1.56)			(0.63)
HML		0.30 **					0.25 *				0.58 ***
		(2.05)					(1.74)				(3.59)
RMW		-0.02					0.14				-0.10
		(-0.11)					(1.15)				(-0.71)
CMA		0.84 ***					0.70 ***				0.37 ***
		(7.00)					(6.22)				(2.85)
MOM		0.56 **					0.82 ***				0.71 ***
		(2.48)					(3.93)				(3.10)
MGMT			0.66 ***					0.65 ***			0.68 ***
			(3.84)					(3.71)			(3.87)
PERF			0.58 **					0.96 ***			1.03 ***
			(2.39)					(4.26)			(4.52)
PEAD				-0.04					0.83 ***		0.42 **
				(-0.20)					(4.60)		(2.15)
FIN				0.24					0.86 ***		1.19 ***
				(1.10)					(4.12)		(4.73)
R_MKT					-0.03					0.24	
					(-0.11)					(0.89)	
R_ME					0.40 ***					0.29 **	0.34 **
					(2.60)					(2.05)	(2.28)
R_IA					0.42 ***					0.37 **	0.63 ***
					(2.58)					(2.32)	(4.41)
R_ROE					0.20					0.44 ***	0.89 ***
					(1.04)					(2.84)	(5.41)
R_EG					1.48 ***					1.46 ***	1.66 ***
					(8.02)					(7.91)	(11.21)
R^2	21	41	43	12	57	28	46	51	44	60	65
MAPE	0.18	0.14	0.14	0.19	0.12	0.17	0.14	0.13	0.15	0.12	0.11
N	904	904	904	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532	532	532	532

Table C.2
War Mimicking Portfolio and Return Premium (Cont.)

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.31	3.39 ***	3.28 ***	4.22 ***	2.11 ***	2.50 ***	-2.02 ***	-1.05 **	-2.37 ***	-2.00 ***	-1.37 **
	(1.04)	(6.80)	(7.51)	(6.07)	(2.73)	(7.93)	(-4.20)	(-2.56)	(-4.03)	(-3.85)	(-2.30)
WMP	-2.01 ***					-2.86 ***	-3.12 ***	-3.28 ***	-3.27 ***	-3.27 ***	-3.25 ***
	(-5.61)					(-9.79)	(-10.79)	(-11.35)	(-11.14)	(-11.31)	(-11.21)
MKT		-3.39 ***	-3.24 ***	-3.86 ***		-2.34 ***	2.42 ***	1.53 ***	2.71 ***		1.68 ***
		(-6.06)	(-6.40)	(-5.47)		(-6.05)	(4.64)	(3.38)	(4.41)		(2.68)
SMB		0.18	0.12				-0.49 ***	-0.81 ***			-0.05
		(1.04)	(0.64)				(-2.89)	(-4.67)			(-0.24)
HML		1.31 ***					0.14				0.49
		(6.24)					(0.72)				(1.56)
RMW		0.20					1.80 ***				0.76 **
		(0.95)					(8.04)				(2.55)
CMA		0.28 *					-0.07				0.08
		(1.81)					(-0.37)				(0.31)
MOM		0.21					1.29 ***				0.90 ***
		(0.86)					(5.40)				(3.19)
MGMT			1.32 ***					1.01 ***			-0.19
			(7.13)					(5.00)			(-0.58)
PERF			0.03					1.22 ***			1.81 ***
			(0.11)					(4.14)			(3.28)
PEAD				-0.56 **					1.01 ***		1.05 **
				(-2.09)					(3.38)		(2.28)
FIN				0.83 **					2.45 ***		1.63 ***
				(2.54)					(7.17)		(2.74)
R_MKT					-1.76 **					2.52 ***	
					(-2.17)					(4.39)	
R_ME					-0.15					-0.26	0.45 **
					(-0.66)					(-1.39)	(2.15)
R_IA					0.24					0.45 **	0.04
					(0.93)					(2.50)	(0.14)
R_ROE					-0.17					1.73 ***	2.61 ***
					(-0.41)					(7.35)	(5.48)
R_EG					3.39 ***					1.01 ***	3.12 ***
					(5.95)					(2.65)	(6.75)
R^2	38	41	40	35	58	58	78	71	76	80	88
MAPE	0.59	0.49	0.49	0.53	0.45	0.42	0.33	0.39	0.36	0.33	0.22
N	360	360	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532	532	532

Table C.2
War Mimicking Portfolio and Return Premium (Cont.)

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include constructed anomaly portfolios in Panel A and constructed nonlinear portfolios in Panel B. "WMP" is the *War* mimicking portfolio; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD" and "FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_MKT, R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. Reported are monthly Return Premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.06 **	0.02	0.04	-0.02	0.00	0.06 **	0.01	0.01	0.02	-0.02	-0.02
	(2.11)	(1.08)	(1.58)	(-0.79)	(0.03)	(2.10)	(0.35)	(0.55)	(0.50)	(-0.53)	(-0.58)
WMP	-2.29 ***					-2.31 ***	-3.30 ***	-2.91 ***	-2.86 ***	-2.53 ***	-3.13 ***
	(-4.04)					(-4.07)	(-7.11)	(-6.30)	(-4.78)	(-4.70)	(-5.76)
MKT		0.09	0.41	0.82 **		-0.53	0.63 **	0.80 ***	0.55 *		0.74 **
		(0.33)	(1.48)	(2.51)		(-1.57)	(2.20)	(2.70)	(1.66)		(2.08)
SMB		0.24	0.34 **				-0.22	0.03			-0.21
		(1.57)	(2.00)				(-1.38)	(0.16)			(-1.19)
HML		0.33 **					0.31 *				0.42 **
		(2.16)					(1.96)				(2.33)
RMW		0.09					0.13				-0.07
		(0.74)					(1.03)				(-0.46)
CMA		0.26 ***					0.21 **				0.30 **
		(2.62)					(1.98)				(2.34)
MOM		0.74 ***					0.99 ***				0.43 *
		(3.50)					(4.48)				(1.84)
MGMT			0.50 ***					0.37 **			0.51 ***
			(3.26)					(2.30)			(2.82)
PERF			0.63 ***					0.90 ***			0.25
			(2.86)					(3.93)			(0.90)
PEAD				0.47 ***					0.81 ***		1.12 ***
				(2.91)					(4.55)		(4.45)
FIN				0.42 **					0.68 ***		0.83 ***
				(2.08)					(3.30)		(3.14)
R_MKT					0.50					0.77 **	
					(1.59)					(2.40)	
R_ME					0.51 ***					0.33	0.33 *
					(2.59)					(1.51)	(1.71)
R_IA					0.33 ***					0.28 **	0.34 ***
					(2.70)					(2.32)	(2.65)
R_ROE					0.15					0.27 *	0.37 **
					(0.97)					(1.86)	(2.33)
R_EG					1.26 ***					1.23 ***	1.30 ***
					(7.43)					(7.09)	(8.11)
R^2	20	23	30	14	47	20	39	42	45	53	58
MAPE	0.34	0.29	0.28	0.33	0.25	0.34	0.26	0.27	0.26	0.25	0.25
N	128	128	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532	532	532

Table C.2
War Mimicking Portfolio and Return Premium (Cont.)

Panel B: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	0.95 ***	0.96 ***	1.03 ***	1.37 ***	1.02 ***	1.79 ***	0.42 **	0.44 **	0.24	0.43 **	0.36 *
	(3.58)	(4.72)	(5.07)	(5.28)	(4.71)	(7.10)	(2.52)	(2.28)	(1.39)	(2.34)	(1.96)
WMP	-0.26					-0.86 **	-1.28 ***	-1.30 ***	-1.46 ***	-1.49 ***	-1.52 ***
	(-0.57)					(-2.57)	(-3.91)	(-3.94)	(-4.26)	(-4.46)	(-4.61)
MKT		-0.29	-0.32	-0.29		-0.88 ***	0.37	0.49 *	0.74 ***		0.44
		(-0.96)	(-1.04)	(-0.94)		(-2.87)	(1.43)	(1.83)	(2.65)		(1.61)
SMB		0.32 *	0.32				0.01	-0.12			0.06
		(1.84)	(1.61)				(0.04)	(-0.71)			(0.37)
HML		0.15					0.26				0.21
		(0.91)					(1.56)				(1.28)
RMW		0.23					0.50 ***				0.28 **
		(1.46)					(3.69)				(2.07)
CMA		0.57 ***					0.53 ***				0.51 ***
		(4.98)					(4.56)				(4.54)
MOM		0.53 **					0.76 ***				0.65 ***
		(2.33)					(3.49)				(2.90)
MGMT			0.48 ***					0.66 ***			0.60 ***
			(2.90)					(4.05)			(3.77)
PERF			0.58 **					0.80 ***			1.13 ***
			(2.36)					(3.23)			(4.67)
PEAD				0.29 *					0.61 ***		0.10
				(1.70)					(3.32)		(0.65)
FIN				0.38					1.09 ***		1.11 ***
				(1.52)					(4.95)		(5.01)
R_MKT					-0.26					0.37	
					(-0.87)					(1.37)	
R_ME					0.29 *					0.16	0.08
					(1.72)					(0.97)	(0.50)
R_IA					0.33 **					0.45 ***	0.36 ***
					(2.51)					(3.59)	(3.07)
R_ROE					0.24					0.66 ***	0.59 ***
					(1.27)					(4.28)	(4.01)
R_EG					0.88 ***					0.78 ***	0.73 ***
					(4.48)					(3.94)	(5.04)
R^2	1	48	46	30	48	30	57	57	52	57	61
MAPE	0.10	0.07	0.07	0.09	0.07	0.09	0.07	0.07	0.07	0.07	0.07
N	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532	532	532

D More Comparisons with Other Factors

In this this appendix, we further explore the characteristics of WarFac. Table 4 illustrates that WarFac captures effects not captured by the news-based VIX related to war (NVIX_War), and the Geopolitical Risk Index (GPR) as measured by Caldara and Iacoviello (2022).

D.1 Correlations with Traded Factors and Industry Portfolios

We first explore the contemporaneous relationship between WarFac and stock returns—for the overall market, various industry sectors, other traded factors, and specifically during times of elevated war risk, as indicated by spikes in war risk.

The findings, detailed in Table D.1, reveal that among traded factors, WarFac has the highest correlation with SMB at 10.9%. WarFac has the lowest correlation among traded factors with CMA at -13.4%, with MGMT and FIN following closely at -12.4% and -11.4%, respectively. The correlations between WarFac and other factors are relatively low, all falling below 10% in absolute terms. Specifically, the correlation between WarFac and the market factor is about 5%, consistent across general and high war risk periods.

When looking at the 12 Fama-French industry portfolios, WarFac displays the highest correlation with the Chemistry sector at 4%, with the Durables and Manufacturing sectors trailing behind. Generally, WarFac exhibits only a modest correlation with the returns of industry portfolios.

D.2 Beta Factors

Next, we explore what kind of tail risk WarFac captures. We estimate the return premium of WarFac compared to other downside risk betas. We perform two-pass tests comparing war risk with the other betas that capture downside risk including CAPM beta, bear beta (Lu and Murray, 2019), downside beta (Ang, Chen, and Xing 2006), relative downside beta (Ang, Chen, and Xing 2006), VIX beta (Ang et al. 2006), volatility beta (Cremers, Halling, and Weinbaum 2015), jump beta (Cremers, Halling, and Weinbaum 2015), coskewness (Harvey and Siddique 2000), skewness beta (Chang, Christoffersen, and Jacobs 2013), tail beta (Kelly and Jiang 2014), and idiosyncratic volatility (Ang et al. 2006).

We form mimicking portfolios using these betas by longing the top decile and shorting the bottom decile sorted on stock-level betas. When we include all of these together with WarFac, WarFac remains significant, and continues to have a pronounced effect on asset returns. This suggests that the market has a concern for war risk above and beyond what is captured by the other kinds of downside risks. Notably, under HXZ's single-sorted and nonlinear portfolio, WarFac is the only tail risk with a significant beta return premium. In contrast, jump, skew, and bear betas for CZ portfolios also show return premia alongside WarFac. For the tree portfolios, VIX beta, and in the case of anomalies, relative downside and jump betas, display significant return premia in addition to WarFac. These results are detailed in Table D.2.

D.3 Textual Factors

In the analysis detailed in Subsection 7.4, we evaluate the pricing power of WarFac, derived using sLDA, against a war-related factor developed through unsupervised LDA, based on topics constructed by Bybee et al. (2024). Since Bybee et al. (2024) do not have a specific war topic, we create a composite war index from their war-related topics, calculating this on a rolling monthly basis.

We also incorporate topics on Financial Crisis and Recession from Bybee et al. (2024), creating two additional factors using a similar approach. The importance of these topics is emphasized by Bybee et al. (2024). For a fair comparison, we normalize these unsupervised factors to have the same standard deviation as WarFac.

Our analysis incorporates four factors: WarFac, the unsupervised war factor, and the Financial Crisis and Recession factors, into a two-pass testing framework. The findings, presented in Table D.3, illustrate that the unsupervised machine learning-derived factors do not display asset pricing power in either univariate tests (columns 2 to 4) or the comprehensive kitchen sink test (column 5). In contrast, WarFac significantly predicts asset returns, with a substantial negative return premium across both test categories. See Table D.3 for the results.

D.4 All sLDA Topic Factors

In Figure 3, we observe two types of downturns of *War*: reversals following spikes, and sharp declines without previous increases. The latter may indicate sudden resolutions of geopolitical tensions, but may alternatively indicate sudden distractions derived from unrelated shocks. Since these possibilities seem quite different, we perform tests to separately measure the effects of upward and downward movements in war in WarFac on the return premium.

Except for the CZ and tree-based portfolios as test assets, we find significant and substantial return premia for both WarFac and WarFac^{-} (indicating reduced coverage), even after accounting for other news topics in our tests (see Table D.4 and Table D.5).[7] To be specific, the return premium of WarFac is still negative and strongly significant after controlling for factors constructed from other news topics.

This suggests the return premium of WarFac is specifically connected to war risk rather than distraction caused by attention to unrelated news. The WarFac^{-}'s premium is generally robust, with the exception of the case of tree portfolios.

[7] WarFac^{-} are derived from negative innovations of an AR(1) model applied to *War*, respectively; see the formal definition on 32

Table D.1

Correlations with Traded Factors and Industry Portfolios

This table reports the correlations between WarFac and traded factors in Panel A and 12 industry portfolios in Panel B. "WarFac" is the innovation in *War* derived from rolling estimation of an AR(1) process; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD" and "FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_MKT, R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. The sample for traded factors (industry portfolios) is from July 1972 (January 1927) to December 2016. Correlations are in percent. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Correlations with Traded Factors

	WarFac	MKT	SMB	HML	RMW	CMA	MOM	MGMT	PERF	PEAD	FIN	R_ME	R_IA	R_ROE	R_EG
WarFac		5.0	10.9	-8.8	-3.1	-13.4	-3.6	-12.4	-2.1	-0.5	-11.4	6.7	-10.3	-3.8	-9.0
MKT	5.0		25.2	-27.4	-25.5	-39.2	-16.1	-52.0	-27.8	-10.9	-50.9	22.8	-36.6	-20.2	-43.5
SMB	10.9	25.2		-21.0	-45.0	-12.5	-2.3	-38.6	-13.0	2.5	-49.5	94.8	-23.3	-38.9	-41.7
HML	-8.8	-27.4	-21.0		15.1	68.8	-18.7	71.7	-31.0	-16.2	63.4	-3.0	67.6	-11.1	18.7
RMW	-3.1	-25.5	-45.0	15.1		4.8	9.9	28.2	43.9	-9.9	58.1	-38.7	15.4	66.9	46.9
CMA	-13.4	-39.2	-12.5	68.8	4.8		0.1	76.7	-5.7	-0.1	59.2	-1.9	90.5	-6.4	29.5
MOM	-3.6	-16.1	-2.3	-18.7	9.9	0.1		5.4	71.5	47.2	9.5	-1.5	3.0	49.8	34.3
MGMT	-12.4	-52.0	-38.6	71.7	28.2	76.7	5.4		2.1	0.5	79.6	-27.2	76.2	10.3	50.8
PERF	-2.1	-27.8	-13.0	-31.0	43.9	-5.7	71.5	2.1		38.2	17.9	-14.6	-5.0	64.7	48.4
PEAD	-0.5	-10.9	2.5	-16.2	-9.9	-0.1	47.2	0.5	38.2		-3.9	0.1	-3.9	22.3	20.3
FIN	-11.4	-50.9	-49.5	63.4	58.1	59.2	9.5	79.6	17.9	-3.9		-38.3	65.4	34.3	55.1
R_ME	6.7	22.8	94.8	-3.0	-38.7	-1.9	-1.5	-27.2	-14.6	0.1	-38.3		-11.8	-32.0	-35.0
R_IA	-10.3	-36.6	-23.3	67.6	15.4	90.5	3.0	76.2	-5.0	-3.9	65.4	-11.8		6.0	35.7
R_ROE	-3.8	-20.2	-38.9	-11.1	66.9	-6.4	49.8	10.3	64.7	22.3	34.3	-32.0	6.0		53.9
R_EG	-9.0	-43.5	-41.7	18.7	46.9	29.5	34.3	50.8	48.4	20.3	55.1	-35.0	35.7	53.9	

Panel B: Correlations with Industry Portfolios

	WarFac	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
WarFac		1.3	3.6	3.5	1.9	4.0	3.5	-0.3	2.8	0.9	3.6	2.1	3.0
NoDur	1.3		73.7	82.7	61.8	82.8	73.1	68.0	70.5	86.3	79.2	83.1	80.9
Durbl	3.6	73.7		86.6	61.8	81.3	77.9	62.5	60.8	79.5	63.5	79.9	79.2
Manuf	3.5	82.7	86.6		73.2	89.0	86.3	67.0	67.7	83.8	73.4	86.9	91.6
Enrgy	1.9	61.8	61.8	73.2		68.5	61.5	51.5	61.0	58.9	56.3	67.6	69.0
Chems	4.0	82.8	81.3	89.0	68.5		79.6	65.8	67.7	80.6	75.7	81.7	81.2
BusEq	3.5	73.1	77.9	86.3	61.5	79.6		67.2	62.4	79.1	71.5	78.9	81.6
Telcm	-0.3	68.0	62.5	67.0	51.5	65.8	67.2		62.8	67.6	60.2	70.6	67.5
Utils	2.8	70.5	60.8	67.7	61.0	67.7	62.4	62.8		64.7	61.6	75.8	67.5
Shops	0.9	86.3	79.5	83.8	58.9	80.6	79.1	67.6	64.7		74.2	83.0	80.9
Hlth	3.6	79.2	63.5	73.4	56.3	75.7	71.5	60.2	61.6	74.2		75.0	71.3
Money	2.1	83.1	79.9	86.9	67.6	81.7	78.9	70.6	75.8	83.0	75.0		86.5
Other	3.0	80.9	79.2	91.6	69.0	81.2	81.6	67.5	67.5	80.9	71.3	86.5	

Table D.2
***War* Factor and Beta Factors**

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. "WarFac" is the innovation in *War* derived from rolling estimation of an AR(1) process. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.14 **	0.14 **	0.15 ***	0.14 **	0.13 **	0.17 **	0.15 **	0.18 *	0.14 *	0.14 **	0.15 **	0.12 **
	(2.36)	(2.40)	(2.93)	(2.27)	(1.99)	(2.57)	(2.54)	(1.77)	(1.93)	(2.19)	(2.38)	(2.57)
WarFac	-0.81 ***	-0.79 ***	-0.79 *	-0.86 **	-0.54 **	-0.71 **	-0.97 ***	-0.79 **	-0.67 **	-0.93 ***	-0.83 ***	-0.33 **
	(-3.56)	(-2.96)	(-1.94)	(-2.57)	(-2.10)	(-2.22)	(-2.64)	(-2.32)	(-2.00)	(-3.63)	(-2.88)	(-2.00)
CAPMBeta	0.18											-1.02
	(0.20)											(-1.05)
DownsideBeta		-0.15										-1.13
		(-0.18)										(-1.03)
RelativeDownsideBeta			-0.39									0.29
			(-0.42)									(0.28)
VIXBeta				0.39								0.32
				(0.29)								(0.42)
VolBeta					-0.64							-1.09
					(-0.59)							(-1.31)
JumpBeta						0.76						-1.19
						(0.67)						(-1.29)
CoSkew							-0.14					0.68
							(-0.11)					(0.90)
SkewBeta								-0.63				-1.42
								(-0.36)				(-1.43)
TailBeta									0.65			0.36
									(0.65)			(0.44)
IVol										-0.53		-0.10
										(-0.60)		(-0.08)
BearBeta											-0.58	-1.88 **
											(-0.76)	(-2.02)
R^2	44	44	45	46	42	42	49	42	41	46	46	57
MAPE	0.23	0.23	0.23	0.23	0.27	0.26	0.22	0.33	0.28	0.22	0.23	0.27
N	187	187	187	187	187	187	187	187	187	187	187	187
T	224	224	224	224	184	184	224	133	181	224	225	133

Table D.2
War Factor and Beta Factors (Cont.)

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.76 ***	0.75 ***	0.72 **	0.72 **	0.60 *	0.54	0.72 **	0.45	0.51	0.71 ***	0.72 **	0.50 *
	(2.61)	(2.62)	(2.29)	(2.41)	(1.85)	(1.39)	(2.19)	(1.11)	(1.33)	(2.64)	(2.56)	(1.90)
WarFac	-0.56 ***	-0.57 ***	-0.59 ***	-0.60 ***	-0.35 **	-0.39 **	-0.63 ***	-0.40 ***	-0.38 **	-0.60 ***	-0.58 ***	-0.24 *
	(-3.73)	(-3.50)	(-2.64)	(-3.03)	(-2.37)	(-2.26)	(-3.26)	(-2.62)	(-2.21)	(-3.84)	(-3.58)	(-1.84)
CAPMBeta	0.01											-0.62
	(0.01)											(-0.68)
DownsideBeta		-0.16										-0.65
		(-0.19)										(-0.63)
RelativeDownsideBeta			-0.14									0.25
			(-0.15)									(0.30)
VIXBeta				0.00								0.41
				(0.00)								(0.64)
VolBeta					-0.46							-0.92
					(-0.47)							(-1.28)
JumpBeta						0.10						-0.87
						(0.10)						(-1.06)
CoSkew							0.09					0.25
							(0.09)					(0.43)
SkewBeta								0.09				-0.47
								(0.08)				(-0.74)
TailBeta									0.07			-0.24
									(0.08)			(-0.34)
IVol										-0.52		-0.16
										(-0.62)		(-0.14)
BearBeta											-0.48	-1.27
											(-0.68)	(-1.47)
R^2	23	23	23	23	18	13	23	12	13	23	24	30
MAPE	0.11	0.11	0.11	0.11	0.13	0.14	0.11	0.17	0.14	0.11	0.11	0.15
N	1843	1843	1843	1843	1843	1843	1843	1843	1843	1843	1843	1843
T	224	224	224	224	184	184	224	133	181	224	225	133

Table D.2
War Factor and Beta Factors (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	1.12 ***	1.04 ***	0.95 **	0.94 **	0.83 *	0.74	0.91 **	0.65	0.73	0.98 ***	0.96 ***	0.68 **
	(3.31)	(2.88)	(2.12)	(2.47)	(1.94)	(1.38)	(2.35)	(1.12)	(1.33)	(2.74)	(2.59)	(2.46)
WarFac	-0.89 **	-0.94 ***	-1.01 ***	-1.00 ***	-0.68 **	-0.67 ***	-1.05 ***	-0.82 **	-0.67 **	-0.99 ***	-0.95 ***	-0.33 *
	(-2.57)	(-2.68)	(-3.17)	(-3.12)	(-2.49)	(-2.60)	(-3.00)	(-2.42)	(-2.55)	(-3.02)	(-2.59)	(-1.74)
CAPMBeta	-0.23											-1.78 *
	(-0.19)											(-1.77)
DownsideBeta		-0.33										-1.26
		(-0.32)										(-1.15)
RelativeDownsideBeta			-0.04									0.55
			(-0.03)									(0.62)
VIXBeta				0.06								0.12
				(0.03)								(0.15)
VolBeta					-0.48							-1.61 *
					(-0.34)							(-1.81)
JumpBeta						-0.30						-2.83 ***
						(-0.22)						(-2.94)
CoSkew							0.17					-1.23
							(0.10)					(-1.51)
SkewBeta								0.83				-2.27 ***
								(0.55)				(-2.89)
TailBeta									-0.06			-0.10
									(-0.06)			(-0.11)
IVol										-0.95		-0.19
										(-1.09)		(-0.16)
BearBeta											-0.74	-2.95 ***
											(-0.88)	(-3.06)
R^2	28	27	26	26	23	21	27	25	19	26	25	51
MAPE	0.16	0.16	0.17	0.16	0.19	0.19	0.16	0.21	0.19	0.16	0.17	0.17
N	1189	1189	1189	1189	1189	1189	1189	1189	1189	1189	1189	1189
T	224	224	224	224	184	184	224	133	181	224	225	133

Table D.2
War Factor and Beta Factors (Cont.)

Panel D: ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	1.03 **	1.04 **	0.93	0.87 *	0.64	0.57	0.96 **	0.15	0.45	0.97 **	0.97 **	0.75 *
	(2.20)	(2.25)	(1.41)	(1.73)	(1.23)	(0.52)	(2.01)	(0.17)	(0.51)	(2.15)	(2.21)	(1.75)
WarFac	-1.63 **	-1.64 **	-1.72 ***	-1.68 ***	-1.35 ***	-1.54 **	-1.62 **	-1.30 ***	-1.15 ***	-1.69 ***	-1.72 ***	-0.89 ***
	(-2.36)	(-2.54)	(-3.25)	(-3.13)	(-2.63)	(-2.57)	(-2.30)	(-2.74)	(-2.98)	(-3.12)	(-2.66)	(-3.49)
CAPMBeta	0.03											-0.76
	(0.01)											(-0.53)
DownsideBeta		-0.56										0.19
		(-0.31)										(0.13)
RelativeDownsideBeta			-0.84									1.63
			(-0.44)									(1.43)
VIXBeta				-0.30								5.01 ***
				(-0.08)								(3.55)
VolBeta					-0.45							0.96
					(-0.16)							(0.86)
JumpBeta						1.75						-0.14
						(0.96)						(-0.11)
CoSkew							1.44					0.36
							(0.59)					(0.28)
SkewBeta								0.22				-1.11
								(0.09)				(-0.86)
TailBeta									1.13			-0.28
									(0.79)			(-0.22)
IVol										-1.76		-2.75 *
										(-1.62)		(-1.92)
BearBeta											-1.47	-1.12
											(-1.00)	(-0.89)
R^2	76	76	75	75	63	67	76	69	70	75	75	87
MAPE	0.27	0.27	0.27	0.27	0.39	0.36	0.27	0.38	0.34	0.27	0.27	0.24
N	360	360	360	360	360	360	360	360	360	360	360	360
T	224	224	224	224	184	184	224	133	181	224	225	133

Table D.2
War Factor and Beta Factors (Cont.)

Panel E: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.05	0.02	-0.01	0.06	0.05	0.03	0.07	0.11	0.04	0.03	0.03	0.16 ***
	(0.69)	(0.31)	(-0.11)	(0.76)	(0.60)	(0.58)	(0.76)	(1.20)	(0.62)	(0.43)	(0.35)	(2.77)
WarFac	-1.35 ***	-1.44 ***	-1.28 ***	-1.18 ***	-1.08 ***	-0.84 **	-1.55 ***	-0.95 **	-0.86 **	-1.56 ***	-1.59 ***	-0.94 ***
	(-4.93)	(-4.72)	(-3.15)	(-2.98)	(-3.69)	(-2.08)	(-4.18)	(-2.01)	(-2.20)	(-4.76)	(-4.57)	(-3.32)
CAPMBeta	1.57											1.21
	(1.34)											(1.17)
DownsideBeta		1.12										1.26
		(1.05)										(0.95)
RelativeDownsideBeta			1.41									3.46 ***
			(1.04)									(3.05)
VIXBeta				2.43								2.57 **
				(1.08)								(2.07)
VolBeta					1.10							0.28
					(0.65)							(0.23)
JumpBeta						-1.17						-2.93 **
						(-0.83)						(-2.49)
CoSkew							-1.69					-1.47 *
							(-0.82)					(-1.76)
SkewBeta								2.17				-1.47
								(0.88)				(-1.37)
TailBeta									-1.32			0.01
									(-1.04)			(0.01)
IVol										-0.01		-0.41
										(-0.01)		(-0.32)
BearBeta											0.17	-1.69
											(0.17)	(-1.51)
R^2	29	34	38	36	28	25	43	24	26	40	38	42
MAPE	0.40	0.39	0.38	0.37	0.43	0.40	0.39	0.44	0.42	0.38	0.38	0.44
N	177	177	177	177	177	177	177	177	177	177	177	177
T	224	224	224	224	184	184	224	133	181	224	225	133

Table D.2
War Factor and Beta Factors (Cont.)

Panel F: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	1.35 ***	1.31 ***	1.16 ***	1.21 ***	1.03 **	0.90 *	1.24 ***	0.83 *	0.87 *	1.28 ***	1.26 ***	1.00 ***
	(3.88)	(3.78)	(2.69)	(3.32)	(2.57)	(1.68)	(3.64)	(1.70)	(1.66)	(3.63)	(3.69)	(3.82)
WarFac	-0.83 **	-0.86 ***	-0.95 ***	-0.94 ***	-0.61 **	-0.61 ***	-0.88 ***	-0.65	-0.54 *	-0.92 ***	-0.84 ***	-0.36 ***
	(-2.50)	(-2.76)	(-3.40)	(-3.34)	(-2.43)	(-2.73)	(-2.98)	(-1.60)	(-1.70)	(-3.29)	(-2.79)	(-2.64)
CAPMBeta	-0.48											-1.62 *
	(-0.38)											(-1.68)
DownsideBeta		-0.68										-1.12
		(-0.65)										(-1.09)
RelativeDownsideBeta			-0.87									1.11
			(-0.59)									(1.29)
VIXBeta				-0.94								0.41
				(-0.41)								(0.59)
VolBeta					-0.78							-1.26
					(-0.53)							(-1.59)
JumpBeta						0.52						-1.50 *
						(0.35)						(-1.75)
CoSkew							1.38					0.52
							(0.78)					(0.79)
SkewBeta								0.76				-0.18
								(0.56)				(-0.23)
TailBeta									0.36			0.44
									(0.43)			(0.58)
IVol										-1.33		-0.38
										(-1.44)		(-0.31)
BearBeta											-1.14	-1.72 *
											(-1.30)	(-1.92)
R^2	43	43	37	35	34	23	38	25	23	41	42	50
MAPE	0.08	0.09	0.09	0.09	0.10	0.11	0.09	0.12	0.11	0.09	0.09	0.10
N	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	224	224	224	224	184	184	224	133	181	224	225	133

Table D.3
War Factor and Unsupervised Topic Factors

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}_{it}^e = \lambda_0 + \beta_{if}'\lambda_f + e_i,$$

where $\bar{R}_{it}^e$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. "WarFac" is innovation in *War* derived from rolling estimation of an AR(1) process and other factors are innovations derived from rolling estimation of an AR(1) process on unsupervised topics in Bybee, Kelly, and Su (2023). Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.17 ***	0.23 ***	0.25 ***	0.20 ***	0.15 ***
	(2.76)	(6.58)	(4.29)	(4.69)	(3.49)
WarFac	-1.10 ***				-1.06 ***
	(-2.69)				(-3.26)
Bybee_War		-0.00			-0.44
		(-0.01)			(-1.13)
Bybee_Financial_crisis			0.45 *		0.05
			(1.67)		(0.22)
Bybee_Recession				0.31 *	-0.03
				(1.94)	(-0.15)
R^2	55	-1	12	25	57
MAPE	0.20	0.32	0.30	0.27	0.19
N	177	177	177	177	177
T	385	385	385	385	385

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.80 ***	0.74 ***	0.80 ***	1.00 ***	0.83 ***
	(3.28)	(3.56)	(4.54)	(4.62)	(3.48)
WarFac	-0.66 **				-0.60 ***
	(-2.16)				(-3.99)
Bybee_War		0.05			-0.22
		(0.26)			(-1.32)
Bybee_Financial_crisis			0.10		-0.14
			(0.51)		(-1.07)
Bybee_Recession				0.15	0.04
				(1.03)	(0.25)
R^2	24	0	1	10	28
MAPE	0.10	0.11	0.11	0.10	0.09
N	1752	1752	1752	1752	1752
T	385	385	385	385	385

Table D.3
***War* Factor and Unsupervised Topic Factors (Cont.)**

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.90 ***	0.82 ***	1.07 ***	1.23 ***	1.10 ***
	(2.81)	(3.85)	(5.61)	(4.80)	(3.59)
WarFac	-0.82 ***				-0.74 **
	(-2.90)				(-2.54)
Bybee_War		0.09			-0.10
		(0.25)			(-0.39)
Bybee_Financial_crisis			0.35		0.02
			(1.15)		(0.10)
Bybee_Recession				0.20	-0.00
				(1.19)	(-0.02)
R^2	15	0	4	8	20
MAPE	0.17	0.20	0.19	0.19	0.17
N	1050	1050	1050	1050	1050
T	385	385	385	385	385

Panel D: ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)
Intercept	0.63	-0.06	0.48 **	1.79 ***	1.45 *
	(0.77)	(-0.16)	(2.04)	(5.20)	(1.91)
WarFac	-2.41 ***				-2.14 ***
	(-3.44)				(-2.92)
Bybee_War		-1.02			-0.93 *
		(-1.48)			(-1.71)
Bybee_Financial_crisis			0.01		-0.62
			(0.03)		(-1.44)
Bybee_Recession				0.52 **	0.49
				(2.26)	(1.08)
R^2	65	9	-0	14	74
MAPE	0.38	0.67	0.65	0.62	0.34
N	360	360	360	360	360
T	385	385	385	385	385

Table D.3
***War* Factor and Unsupervised Topic Factors (Cont.)**

Panel E: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)
Intercept	0.12 **	0.07	0.07 *	0.07 *	0.10
	(2.41)	(1.38)	(1.86)	(1.89)	(1.64)
WarFac	-1.10 **				-1.51 ***
	(-2.11)				(-4.19)
Bybee_War		-0.14			-0.43
		(-0.40)			(-1.13)
Bybee_Financial_crisis			0.06		0.06
			(0.21)		(0.20)
Bybee_Recession				0.07	-0.47
				(0.39)	(-1.26)
R^2	19	-0	-0	0	28
MAPE	0.36	0.45	0.45	0.44	0.34
N	160	160	160	160	160
T	385	385	385	385	385

Panel F: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)
Intercept	1.00 ***	1.03 ***	1.23 ***	1.46 ***	1.46 ***
	(2.87)	(4.83)	(5.38)	(4.91)	(4.33)
WarFac	-0.80 ***				-0.83 ***
	(-2.92)				(-2.99)
Bybee_War		0.23			-0.26
		(0.54)			(-1.12)
Bybee_Financial_crisis			0.39		0.09
			(1.14)		(0.52)
Bybee_Recession				0.24	0.13
				(1.25)	(0.66)
R^2	18	3	15	20	39
MAPE	0.10	0.10	0.10	0.09	0.08
N	2190	2190	2190	2190	2190
T	385	385	385	385	385

Table D.4
War Factor and All Other sLDA Topic Factors

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}_{it}^{e} = \lambda_0 + \beta_{if}' \lambda_f + e_i,$$

where $\bar{R}_{it}^{e}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. "WarFac" is innovation in *War* derived from rolling estimation of an AR(1) process. Factors for other discourse topics are also innovation derived from rolling estimation of an AR(1) process. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	0.18 ***	0.24 ***	0.16 ***	0.14 ***	0.22 ***	0.18 ***	0.25 ***	0.23 ***	0.22 ***	0.24 ***	0.19 ***	0.25 ***	0.23 ***	0.24 ***	0.11 **
	(2.97)	(6.79)	(2.63)	(2.73)	(4.71)	(3.99)	(5.35)	(6.64)	(5.59)	(7.30)	(5.04)	(6.19)	(5.75)	(7.14)	(2.39)
War	-1.33 ***														-1.11 ***
	(-2.87)														(-2.77)
Pandemic		-0.43													-0.99 **
		(-1.26)													(-2.01)
Panic			-1.23 ***												-0.03
			(-2.69)												(-0.10)
Confidence				1.79 **											0.95 *
				(2.51)											(1.65)
Saving					0.82 **										0.15
					(2.57)										(0.46)
Consumption						-1.15 **									0.13
						(-2.03)									(0.32)
Money							0.77 *								0.42
							(1.96)								(1.03)
Tech								0.06							-0.36
								(0.28)							(-1.22)
Real_estate_boom									-0.43						0.89
									(-1.01)						(1.64)
Real_estate_crash										-0.34					-0.17
										(-0.89)					(-0.41)
Stock_bubble											0.88				0.40
											(1.62)				(0.87)
Stock_crash												0.87			-0.59
												(1.28)			(-0.93)
Boycott													-0.11		-0.17
													(-0.35)		(-0.60)
Wage														0.23	-0.11
														(0.79)	(-0.32)
R^2	48	5	31	19	7	17	11	-1	1	2	7	4	-0	1	72
MAPE	0.26	0.37	0.31	0.33	0.37	0.33	0.35	0.39	0.38	0.38	0.36	0.38	0.39	0.38	0.17
N	138	138	138	138	138	138	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.4
War Factor and All Other sLDA Topic Factors (Cont.)

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	0.76 ***	0.66 ***	0.73 ***	0.76 ***	0.61 ***	0.62 ***	0.73 ***	0.60 ***	0.65 ***	0.61 ***	0.71 ***	0.57 ***	0.61 ***	0.57 ***	0.92 ***
	(3.79)	(3.05)	(3.40)	(3.26)	(3.00)	(2.85)	(4.16)	(3.37)	(3.38)	(3.14)	(3.50)	(2.60)	(3.03)	(2.85)	(3.90)
War	-0.66 **														-0.52 ***
	(-2.25)														(-3.05)
Pandemic		-0.30													-0.50 **
		(-1.19)													(-2.13)
Panic			-0.66 **												-0.29 *
			(-2.26)												(-1.85)
Confidence				1.04 ***											0.50 ***
				(3.43)											(2.86)
Saving					0.32 **										0.07
					(2.09)										(0.45)
Consumption						-0.64 *									-0.06
						(-1.74)									(-0.34)
Money							0.32								-0.02
							(1.32)								(-0.13)
Tech								-0.05							-0.23 *
								(-0.32)							(-1.71)
Real_estate_boom									-0.46						0.23
									(-1.23)						(0.80)
Real_estate_crash										-0.06					0.13
										(-0.25)					(0.76)
Stock_bubble											0.57 **				0.41 **
											(2.12)				(2.20)
Stock_crash												0.58			-0.07
												(1.48)			(-0.34)
Boycott													0.01		0.02
													(0.05)		(0.18)
Wage														0.15	-0.04
														(0.76)	(-0.25)
R^2	20	3	17	13	3	11	4	0	5	0	5	3	-0	1	42
MAPE	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.12	0.11	0.12	0.11	0.11	0.12	0.12	0.09
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.4
War Factor and All Other sLDA Topic Factors (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	1.16 ***	0.74 ***	0.96 ***	0.96 **	0.81 **	0.88 ***	1.04 ***	1.12 ***	0.75 ***	0.76 ***	1.13 ***	0.79 ***	0.81 ***	0.71 ***	1.22 ***
	(3.68)	(3.07)	(3.18)	(2.48)	(2.57)	(3.31)	(3.22)	(4.40)	(3.78)	(3.46)	(3.11)	(3.64)	(3.14)	(3.54)	(4.09)
War	-1.26 ***														-0.44
	(-3.16)														(-1.13)
Pandemic		-0.51													-0.95 **
		(-1.46)													(-2.04)
Panic			-1.02 **												-0.02
			(-2.10)												(-0.06)
Confidence				2.06 **											1.07 **
				(2.51)											(2.24)
Saving					-0.97 **										-0.20
					(-2.40)										(-0.70)
Consumption						-0.94									-0.99 ***
						(-1.49)									(-2.68)
Money							0.74 **								-0.27
							(2.40)								(-0.99)
Tech								0.82 **							0.51 **
								(2.31)							(2.39)
Real_estate_boom									0.27						0.53
									(0.43)						(0.95)
Real_estate_crash										-0.25					0.24
										(-0.58)					(0.80)
Stock_bubble											1.81 ***				1.48 ***
											(3.74)				(4.23)
Stock_crash												0.04			-0.40
												(0.07)			(-0.97)
Boycott													0.21		-0.40 *
													(0.55)		(-1.84)
Wage														0.22	-0.29
														(0.65)	(-0.80)
R^2	22	7	18	18	7	11	14	16	0	0	16	-0	0	1	51
MAPE	0.18	0.18	0.18	0.18	0.19	0.19	0.18	0.18	0.20	0.20	0.19	0.20	0.20	0.20	0.13
N	904	904	904	904	904	904	904	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.4
War Factor and All Other sLDA Topic Factors (Cont.)

Panel D: ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	1.20	0.11	1.23	0.83	0.24	0.83	0.59	1.22	-0.10	-0.23	1.74	0.41 **	0.37	0.15	0.95
	(1.19)	(0.38)	(1.14)	(0.91)	(0.53)	(1.09)	(1.09)	(1.60)	(-0.25)	(-0.30)	(1.31)	(2.04)	(0.64)	(0.71)	(1.37)
War	-3.32 ***														-1.00
	(-3.42)														(-0.97)
Pandemic		-0.99 *													-0.94
		(-1.96)													(-0.92)
Panic			-3.93 ***												-0.94
			(-3.12)												(-0.95)
Confidence				4.82 ***											1.82
				(2.85)											(1.64)
Saving					-1.60										0.77
					(-1.36)										(1.02)
Consumption						-3.76 **									-1.16
						(-1.99)									(-1.37)
Money							1.36 **								-0.13
							(2.45)								(-0.20)
Tech								2.42 ***							0.29
								(3.40)							(0.54)
Real_estate_boom									2.17						1.14
									(1.59)						(0.99)
Real_estate_crash										-3.03					-0.46
										(-1.42)					(-0.64)
Stock_bubble											6.41 ***				3.59 ***
											(3.14)				(3.92)
Stock_crash												-0.26			-0.07
												(-0.25)			(-0.07)
Boycott													-1.38		-1.92 **
													(-1.14)		(-2.47)
Wage														0.37	-0.10
														(0.92)	(-0.13)
R^2	62	9	46	28	6	30	20	25	10	20	74	-0	4	1	90
MAPE	0.44	0.72	0.51	0.55	0.70	0.60	0.67	0.61	0.70	0.67	0.35	0.70	0.69	0.71	0.21
N	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.4
War Factor and All Other sLDA Topic Factors (Cont.)

Panel E: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	0.04	-0.01	0.02	-0.04	-0.01	0.01	-0.00	0.02	-0.02	-0.02	-0.03	-0.01	-0.02	-0.01	-0.02
	(0.83)	(-0.24)	(0.48)	(-0.67)	(-0.31)	(0.17)	(-0.06)	(0.59)	(-0.50)	(-0.50)	(-0.55)	(-0.19)	(-0.43)	(-0.27)	(-0.30)
War	-1.02 **														-1.12 **
	(-2.12)														(-2.33)
Pandemic		-0.32													-0.84
		(-0.91)													(-1.30)
Panic			-0.98 *												-0.96 **
			(-1.94)												(-2.48)
Confidence				1.44 *											1.31 **
				(1.84)											(2.17)
Saving					0.33										0.24
					(0.87)										(0.51)
Consumption						-0.57									-0.21
						(-1.10)									(-0.39)
Money							0.21								-1.01 **
							(0.64)								(-2.22)
Tech								0.45							0.26
								(1.44)							(0.86)
Real_estate_boom									0.40						1.33 *
									(0.72)						(1.92)
Real_estate_crash										0.09					0.78
										(0.21)					(1.28)
Stock_bubble											1.36 **				1.33 ***
											(2.28)				(2.76)
Stock_crash												1.20 **			0.73
												(2.10)			(1.01)
Boycott													-0.19		-0.21
													(-0.53)		(-0.65)
Wage														0.05	-0.20
														(0.16)	(-0.45)
R^2	19	1	15	9	0	4	-0	5	0	-1	10	3	-0	-1	53
MAPE	0.32	0.39	0.34	0.35	0.40	0.36	0.39	0.38	0.40	0.40	0.38	0.39	0.40	0.40	0.27
N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.4
War Factor and All Other sLDA Topic Factors (Cont.)

Panel F: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	1.18 ***	0.97 ***	1.09 ***	1.05 ***	0.93 ***	1.04 ***	1.01 ***	1.24 ***	1.02 ***	0.94 ***	1.18 ***	1.01 ***	0.92 ***	1.23 ***	1.42 ***
	(3.60)	(4.39)	(3.59)	(3.14)	(3.50)	(3.52)	(3.60)	(4.50)	(4.84)	(4.13)	(3.51)	(4.10)	(3.41)	(5.39)	(5.14)
War	-0.89 ***														-0.72 ***
	(-3.64)														(-3.55)
Pandemic		0.21													-0.04
		(0.57)													(-0.15)
Panic			-1.04 **												-0.24
			(-2.01)												(-1.37)
Confidence				1.61 *											0.88 ***
				(1.79)											(3.34)
Saving					-0.43 **										-0.38 **
					(-2.49)										(-2.16)
Consumption						-1.12 *									-0.12
						(-1.66)									(-0.53)
Money							0.29								-0.10
							(1.30)								(-0.48)
Tech								0.80 **							0.19
								(2.52)							(1.34)
Real_estate_boom									-0.53						0.47
									(-0.84)						(1.18)
Real_estate_crash										0.05					-0.04
										(0.14)					(-0.31)
Stock_bubble											1.52 ***				0.72 ***
											(3.40)				(3.92)
Stock_crash												-0.83			-0.26
												(-1.43)			(-1.22)
Boycott													-0.31		-0.07
													(-0.81)		(-0.48)
Wage														-0.67	-0.52 ***
														(-1.39)	(-2.85)
R^2	16	1	22	23	3	26	2	18	4	-0	17	3	2	16	53
MAPE	0.10	0.10	0.09	0.09	0.10	0.09	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.09	0.07
N	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.5
Negative *War* Factor and All Other sLDA Topic Factors

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. "WarFac_Neg" (i.e. WarFac$^-$) is the negative innovation in *War* derived from rolling estimation of an AR(1) process. Factors for other discourse topics are also innovations derived from rolling estimation of an AR(1) process. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	0.18 ***	0.24 ***	0.16 ***	0.14 ***	0.22 ***	0.18 ***	0.25 ***	0.23 ***	0.22 ***	0.24 ***	0.19 ***	0.25 ***	0.23 ***	0.24 ***	0.12 ***
	(3.25)	(6.79)	(2.63)	(2.73)	(4.71)	(3.99)	(5.35)	(6.64)	(5.59)	(7.30)	(5.04)	(6.19)	(5.75)	(7.14)	(2.87)
WarFac_Neg	-0.69 ***														-0.56 ***
	(-2.94)														(-2.73)
Pandemic		-0.43													-0.88 **
		(-1.26)													(-1.97)
Panic			-1.23 ***												-0.13
			(-2.69)												(-0.43)
Confidence				1.79 **											1.05 **
				(2.51)											(1.96)
Saving					0.82 **										0.12
					(2.57)										(0.38)
Consumption						-1.15 **									0.13
						(-2.03)									(0.33)
Money							0.77 *								0.45
							(1.96)								(1.16)
Tech								0.06							-0.32
								(0.28)							(-1.18)
Real_estate_boom									-0.43						0.68
									(-1.01)						(1.29)
Real_estate_crash										-0.34					-0.27
										(-0.89)					(-0.73)
Stock_bubble											0.88				0.30
											(1.62)				(0.69)
Stock_crash												0.87			-0.33
												(1.28)			(-0.54)
Boycott													-0.11		-0.15
													(-0.35)		(-0.57)
Wage														0.23	-0.03
														(0.79)	(-0.09)
R^2	47	5	31	19	7	17	11	-1	1	2	7	4	-0	1	73
MAPE	0.26	0.37	0.31	0.33	0.37	0.33	0.35	0.39	0.38	0.38	0.36	0.38	0.39	0.38	0.17
N	138	138	138	138	138	138	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.5
Negative *War* Factor and All Other sLDA Topic Factors (Cont.)

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	0.76 ***	0.66 ***	0.73 ***	0.76 ***	0.61 ***	0.62 ***	0.73 ***	0.60 ***	0.65 ***	0.61 ***	0.71 ***	0.57 ***	0.61 ***	0.57 ***	0.93 ***
	(4.03)	(3.05)	(3.40)	(3.26)	(3.00)	(2.85)	(4.16)	(3.37)	(3.38)	(3.14)	(3.50)	(2.60)	(3.03)	(2.85)	(4.10)
WarFac_Neg	-0.30 **														-0.24 **
	(-2.12)														(-2.50)
Pandemic		-0.30													-0.49 **
		(-1.19)													(-2.21)
Panic			-0.66 **												-0.31 **
			(-2.26)												(-2.04)
Confidence				1.04 ***											0.50 ***
				(3.43)											(2.95)
Saving					0.32 **										0.05
					(2.09)										(0.37)
Consumption						-0.64 *									-0.11
						(-1.74)									(-0.66)
Money							0.32								0.01
							(1.32)								(0.08)
Tech								-0.05							-0.22 *
								(-0.32)							(-1.70)
Real_estate_boom									-0.46						0.16
									(-1.23)						(0.56)
Real_estate_crash										-0.06					0.06
										(-0.25)					(0.42)
Stock_bubble											0.57 **				0.39 **
											(2.12)				(2.15)
Stock_crash												0.58			-0.02
												(1.48)			(-0.08)
Boycott													0.01		0.04
													(0.05)		(0.39)
Wage														0.15	0.00
														(0.76)	(0.02)
R^2	15	3	17	13	3	11	4	0	5	0	5	3	-0	1	41
MAPE	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.12	0.11	0.12	0.11	0.11	0.12	0.12	0.09
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.5
Negative *War* Factor and All Other sLDA Topic Factors (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	1.18 ***	0.74 ***	0.96 ***	0.96 **	0.81 **	0.88 ***	1.04 ***	1.12 ***	0.75 ***	0.76 ***	1.13 ***	0.79 ***	0.81 ***	0.71 ***	1.17 ***
	(3.67)	(3.07)	(3.18)	(2.48)	(2.57)	(3.31)	(3.22)	(4.40)	(3.78)	(3.46)	(3.11)	(3.64)	(3.14)	(3.54)	(3.97)
WarFac_Neg	-0.66 ***														-0.36 *
	(-4.27)														(-1.71)
Pandemic		-0.51													-0.89 *
		(-1.46)													(-1.94)
Panic			-1.02 **												-0.00
			(-2.10)												(-0.01)
Confidence				2.06 **											1.16 **
				(2.51)											(2.39)
Saving					-0.97 **										-0.19
					(-2.40)										(-0.67)
Consumption						-0.94									-0.93 **
						(-1.49)									(-2.50)
Money							0.74 **								-0.33
							(2.40)								(-1.17)
Tech								0.82 **							0.45 *
								(2.31)							(1.91)
Real_estate_boom									0.27						0.48
									(0.43)						(0.88)
Real_estate_crash										-0.25					0.09
										(-0.58)					(0.34)
Stock_bubble											1.81 ***				1.32 ***
											(3.74)				(4.11)
Stock_crash												0.04			-0.38
												(0.07)			(-0.94)
Boycott													0.21		-0.42 *
													(0.55)		(-1.89)
Wage														0.22	-0.24
														(0.65)	(-0.69)
R^2	24	7	18	18	7	11	14	16	0	0	16	-0	0	1	53
MAPE	0.18	0.18	0.18	0.18	0.19	0.19	0.18	0.18	0.20	0.20	0.19	0.20	0.20	0.20	0.13
N	904	904	904	904	904	904	904	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.5
Negative *War* Factor and All Other sLDA Topic Factors (Cont.)

Panel D: ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	1.14	0.11	1.23	0.83	0.24	0.83	0.59	1.22	-0.10	-0.23	1.74	0.41 **	0.37	0.15	0.93
	(1.23)	(0.38)	(1.14)	(0.91)	(0.53)	(1.09)	(1.09)	(1.60)	(-0.25)	(-0.30)	(1.31)	(2.04)	(0.64)	(0.71)	(1.35)
WarFac_Neg	-1.63 ***														-0.47
	(-3.45)														(-0.84)
Pandemic		-0.99 *													-0.91
		(-1.96)													(-0.90)
Panic			-3.93 ***												-0.99
			(-3.12)												(-1.02)
Confidence				4.82 ***											1.82
				(2.85)											(1.59)
Saving					-1.60										0.79
					(-1.36)										(1.09)
Consumption						-3.76 **									-1.31
						(-1.99)									(-1.34)
Money							1.36 **								-0.10
							(2.45)								(-0.16)
Tech								2.42 ***							0.36
								(3.40)							(0.68)
Real_estate_boom									2.17						1.14
									(1.59)						(1.00)
Real_estate_crash										-3.03					-0.49
										(-1.42)					(-0.70)
Stock_bubble											6.41 ***				3.58 ***
											(3.14)				(3.68)
Stock_crash												-0.26			-0.21
												(-0.25)			(-0.19)
Boycott													-1.38		-1.95 **
													(-1.14)		(-2.57)
Wage														0.37	-0.06
														(0.92)	(-0.09)
R^2	56	9	46	28	6	30	20	25	10	20	74	-0	4	1	90
MAPE	0.47	0.72	0.51	0.55	0.70	0.60	0.67	0.61	0.70	0.67	0.35	0.70	0.69	0.71	0.21
N	360	360	360	360	360	360	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.5

Negative *War* Factor and All Other sLDA Topic Factors (Cont.)

Panel E: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	0.03	-0.01	0.02	-0.04	-0.01	0.01	-0.00	0.02	-0.02	-0.02	-0.03	-0.01	-0.02	-0.01	-0.02
	(0.55)	(-0.24)	(0.48)	(-0.67)	(-0.31)	(0.17)	(-0.06)	(0.59)	(-0.50)	(-0.50)	(-0.55)	(-0.19)	(-0.43)	(-0.27)	(-0.33)
WarFac_Neg	-0.58 ***														-0.63 ***
	(-2.59)														(-2.66)
Pandemic		-0.32													-0.71
		(-0.91)													(-1.17)
Panic			-0.98 *												-0.86 **
			(-1.94)												(-2.26)
Confidence				1.44 *											1.57 **
				(1.84)											(2.49)
Saving					0.33										0.14
					(0.87)										(0.32)
Consumption						-0.57									-0.12
						(-1.10)									(-0.23)
Money							0.21								-1.02 **
							(0.64)								(-2.32)
Tech								0.45							0.23
								(1.44)							(0.78)
Real_estate_boom									0.40						1.15 *
									(0.72)						(1.66)
Real_estate_crash										0.09					0.50
										(0.21)					(0.91)
Stock_bubble											1.36 **				1.13 ***
											(2.28)				(2.59)
Stock_crash												1.20 **			0.69
												(2.10)			(1.00)
Boycott													-0.19		-0.09
													(-0.53)		(-0.30)
Wage														0.05	-0.19
														(0.16)	(-0.44)
R^2	23	1	15	9	0	4	-0	5	0	-1	10	3	-0	-1	56
MAPE	0.32	0.39	0.34	0.35	0.40	0.36	0.39	0.38	0.40	0.40	0.38	0.39	0.40	0.40	0.27
N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

Table D.5
Negative *War* Factor and All Other sLDA Topic Factors (Cont.)

Panel F: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	1.10 ***	0.97 ***	1.09 ***	1.05 ***	0.93 ***	1.04 ***	1.01 ***	1.24 ***	1.02 ***	0.94 ***	1.18 ***	1.01 ***	0.92 ***	1.23 ***	1.44 ***
	(3.59)	(4.39)	(3.59)	(3.14)	(3.50)	(3.52)	(3.60)	(4.50)	(4.84)	(4.13)	(3.51)	(4.10)	(3.41)	(5.39)	(5.37)
WarFac_Neg	-0.33 **														-0.34 ***
	(-2.42)														(-2.78)
Pandemic		0.21													0.00
		(0.57)													(0.02)
Panic			-1.04 **												-0.27
			(-2.01)												(-1.48)
Confidence				1.61 *											0.94 ***
				(1.79)											(3.51)
Saving					-0.43 **										-0.37 **
					(-2.49)										(-2.17)
Consumption						-1.12 *									-0.21
						(-1.66)									(-0.89)
Money							0.29								-0.04
							(1.30)								(-0.20)
Tech								0.80 **							0.25
								(2.52)							(1.62)
Real_estate_boom									-0.53						0.39
									(-0.84)						(1.00)
Real_estate_crash										0.05					-0.11
										(0.14)					(-0.89)
Stock_bubble											1.52 ***				0.72 ***
											(3.40)				(4.06)
Stock_crash												-0.83			-0.23
												(-1.43)			(-1.07)
Boycott													-0.31		-0.08
													(-0.81)		(-0.59)
Wage														-0.67	-0.57 ***
														(-1.39)	(-2.98)
R^2	8	1	22	23	3	26	2	18	4	-0	17	3	2	16	51
MAPE	0.10	0.10	0.09	0.09	0.10	0.09	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.09	0.08
N	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532	532	532	532	532	532	532

E Robustness

In this section, we perform a battery of robustness checks to confirm the pricing result of WarFac.

E.1 Subsample Results

Figure 3 illustrates notable increases in article frequency at certain points, such as towards the end of the sample period, where there indeed has been a rise in the number of articles. To ensure our result is robust for this unusual pattern, we adjust our analysis timeframe for the two-pass test to span from 1972 to 2011, thereby omitting the final five years of the initial dataset. Although the 1940s are utilized in the rolling estimation of WarFac, this period is not applied in the two-pass test. To further ensure the robustness of our findings and to address concerns related to the data from the 1940s, we also conducted analyses excluding data prior to 1945 and then data prior to 1965 when constructing the war index. Our findings remain consistent across these varied sample periods, indicating that our results are robust to these adjustments. Please see the results in Table E.1.

E.2 Other Specifications of WarFac and WMP

In this section, we explore other specifications of WarFac and WMP to evaluate the robustness of their ability to predict the cross section of future returns.

First, the time series of war index might seems more like an ARMA process instead of the AR(1) process used in our main specification. We therefore consider the alternative of an ARMA(1,1) model here for constructing WarFac. ARMA(1,1) can potentially capture more complex dependencies, at the expense of possible overfitting and loss of parsimony. The return premium of WarFac constructed as the ARMA(1,1) residuals is described in Table E.2.

The performances of WarFac derived from AR(1) and ARMA(1,1) models are similar, though a bit weaker for ARMA(1,1). Comparing the results across six test assets for a two-pass test regression with WarFac as a single factor, the average return premium is -1.25% for ARMA(1,1) versus -1.41% for AR(1), with associated t-statistics of -2.53 versus -2.91, R^2 values of 28% versus 31%, and MAE of 0.26 versus 0.24, respectively, for ARMA(1,1) and AR(1).

In our main analysis, we therefore use WarFac based on AR(1) innovations. This choice is motivated by the principle of parsimony, which favors simpler models to minimize overfitting, which is especially important in our context of monthly re-estimation of WarFac. This approach aligns with the broader literature's use of simpler time series models to avoid overfitting.

Second, we investigate possible differences in meaning of up versus down movements and test whether upward or downward movements in *War* drives the return premium in WarFac. We define WarFac as the innovation from an AR(1) model on *War*, and then consider two component versions of WarFac: WarFac$^+$ (=max(WarFac, 0)), which indicates more news coverage of war, and WarFac$^-$ (=min(WarFac, 0)), which indicates less coverage of *War*. We find that both WarFac$^+$ and WarFac$^-$ price assets and have significant return premia (see the second and third columns under "Positive" and "Negative" in Table E.2).

Lastly, we apply various approaches to construct WMP from *War* to ensure that the results are robust. These approaches are as follows.

First, we use the cross-sectional approach and find that the WMP under this approach generates strong spanning test results (see Table C.1), significant prices of risk (Table C.2), and passes the Protocol of Factor Identification (Table F.2) and the three-pass test (Table G.1). We thus adhere to this approach and present it as our main result. Specifically, Table C.2 shows the WMP generates significant and negative return premiums across most of testing assets. See Section 6 for the description of our mimicking portfolios

To ensure the reliability of our findings, we also present the result of the WMP constructed by the time-series approach. We use two basis assets including (1) 360 value-weighted tree-based portfolios and (2) 30 portfolios (comprising ten equal-weighted book-to-market sorted portfolios, ten equal-weighted size-sorted portfolios, and ten value-weighted momentum-sorted portfolios). In constructing these mimicking portfolios, the R^2 values are 6.4% and 0.7% for (1) and (2), respectively. The intercept for (1) is -0.002 which is insignificant, while for (2), it is 0.001 and significant at the 5% level.[8]

Table E.2 suggests that *War* has a strong correlation with the tree-based portfolios. The results of WMP constructed from the tree-based portfolios in generating a negative and

[8]Given the extensive number of portfolios analyzed (390 in total), for brevity we summarize here only these key findings. Detailed slope coefficients and further statistical analysis are available upon request.

significant return premium remain robust and consistent across all test assets. The return premium of the WMP constructed from 30 equal-weighted portfolios are also negative and significant for all test assets except for single-sorted portfolios from HXZ.

E.3 Choice of Seed Words and Topics

Next, we describe how robust the return premium of WarFac is across the variations of seed words and number of topics used to construct the war index as described below.

1. Base model with seed words as in Table A.1;
2. Added "conflict" and "tension" to *War* in (1);
3. Added "terrorism" and "terrorist" to *War* in (2);
4. Replaced seed words for *Pandemic* in (3) with "contagion, disease, epidemic, epidemiology, infection, outbreak, pandemic, public_health, quarantine, vaccination, vaccine, virus" and added *Natural Disaster* with "catastrophe, cyclone, destruction, drought, earthquake, flood, hurricane, landslide, mortality, natural_disaster, natural_hazard, storm, tornado, traumatic_exposure, tsunami, volcano, wildfire";
5. Replaced *War* in (4) with "army, battalion, battle, bomb, conflict, front_line, gun, military, munition, navy, officer, tension, terror, terrorism, terrorist, war, weapon";
6. Removed duplicates in seed words within and across topics in (5);
7. Estimated (1) with 50 unseeded topics; and
8. Used only one topic *War* with one seed word "war" with 50 unseeded topics.

Table E.3 indicates that WarFac has negative and significant return premium in all models. The specifications based on a single seed word ("war") in specification (1), three seed words ("war, conflict, tension") in specification (2), or five seed words ("war, conflict, tension, terrorism, terrorist") in specification (3) have average MAPEs of 0.23%, 0.27%, and 0.23% across six test assets, respectively. WarFac with one seed word of "war" has a marginally higher MAPE than with five seed words, but the use of one seed word avoids concerns about subjectivity in seed word selection.

Table E.1
Subsample Results

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor return premiums. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D. Panel A (B) uses WarFac constructed with data from 1945 (1965). Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2011. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Using Data after 1945 to Construct WarFac

	HXZ LS	HXZ Single	CZ Single	ML-Based	Own Anomalies	Own Nonlinear
Intercept	0.22 ***	0.64 ***	0.99 ***	0.75	0.05	1.02 ***
	(3.10)	(2.94)	(2.92)	(0.73)	(0.89)	(3.07)
WarFac	-1.37 ***	-0.51 **	-0.95 ***	-2.75 ***	-1.02 **	-0.64 ***
	(-2.63)	(-1.99)	(-3.28)	(-2.74)	(-2.00)	(-2.81)
R^2	44	13	15	34	16	12
MAPE	0.29	0.12	0.19	0.67	0.35	0.10
N	138	1372	904	360	129	2190
T	472	472	472	472	472	472

Panel B: Using Data after 1965 to Construct WarFac

	HXZ LS	HXZ Single	CZ Single	ML-Based	Own Anomalies	Own Nonlinear
Intercept	0.25 ***	0.61 ***	0.91 ***	0.41	0.05	0.96 ***
	(3.48)	(2.78)	(2.71)	(0.53)	(0.92)	(2.99)
WarFac	-1.29 ***	-0.42 *	-0.81 ***	-2.04 **	-1.09 **	-0.51 **
	(-2.60)	(-1.82)	(-3.08)	(-2.31)	(-2.41)	(-2.09)
R^2	34	8	11	19	17	8
MAPE	0.32	0.12	0.20	0.74	0.37	0.10
N	138	1372	904	360	129	2190
T	472	472	472	472	472	472

Table E.2
Other Specifications of WarFac and WMP

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta_{if}\lambda + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the factor exposure of portfolio i estimated via a time-series regression of portfolio return onto factor, and λ_f is the factor return premium. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D, own constructed anomalies in Panel E, and own constructed nonlinear portfolios in Panel F. "ARMA11" is WarFac derived from rolling estimation of AR(1,1) on *War*; "Positive" is positive innovation of *War*; "Negative" is negative innovation of *War*; "WMP_TS_Tree" is WarFac mimicking portfolio constructed using the time-series approach with 360 ML tree portfolios; and "WMP_TS_FF30" is WarFac mimicking portfolio constructed using the time-series approach with Fama-French 30 portfolios. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	ARMA11	Positive	Negative	WMP_TS_Tree	WMP_TS_FF30
Intercept	0.15 ***	0.21 ***	0.18 ***	0.20 ***	0.26 ***
	(2.80)	(3.54)	(3.25)	(3.66)	(7.01)
WarFac	-1.21 **	-0.71 **	-0.69 ***	-0.83 ***	-0.08 **
	(-2.51)	(-2.31)	(-2.94)	(-3.23)	(-2.33)
R^2	36	27	47	52	17
MAPE	0.30	0.32	0.26	0.26	0.34
N	138	138	138	138	138
T	532	532	532	532	532

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	ARMA11	Positive	Negative	WMP_TS_Tree	WMP_TS_FF30
Intercept	0.75 ***	0.69 ***	0.76 ***	0.82 ***	0.79 ***
	(3.95)	(3.17)	(4.03)	(4.51)	(4.37)
WarFac	-0.55 *	-0.40 **	-0.30 **	-0.41 **	-0.05
	(-1.92)	(-2.14)	(-2.12)	(-2.25)	(-1.43)
R^2	13	15	15	20	7
MAPE	0.11	0.11	0.11	0.11	0.11
N	1372	1372	1372	1372	1372
T	532	532	532	532	532

Table E.2
Other Specifications of WarFac and WMP (Cont.)

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	ARMA11	Positive	Negative	WMP_TS_Tree	WMP_TS_FF30
Intercept	1.16 ***	0.97 ***	1.18 ***	1.28 ***	1.08 ***
	(4.54)	(3.34)	(3.67)	(4.59)	(4.22)
WarFac	-1.06 **	-0.61 **	-0.66 ***	-0.80 ***	-0.10 ***
	(-2.45)	(-2.00)	(-4.27)	(-3.51)	(-3.63)
R^2	18	10	24	26	25
MAPE	0.18	0.19	0.18	0.17	0.17
N	904	904	904	904	904
T	532	532	532	532	532

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	ARMA11	Positive	Negative	WMP_TS_Tree	WMP_TS_FF30
Intercept	1.30	1.10	1.14	1.33 *	0.71 *
	(1.57)	(0.87)	(1.23)	(1.67)	(1.82)
WarFac	-2.86 ***	-2.77 ***	-1.63 ***	-1.88 ***	-0.20 ***
	(-3.71)	(-2.87)	(-3.45)	(-4.39)	(-4.40)
R^2	48	57	56	60	27
MAPE	0.50	0.47	0.47	0.45	0.62
N	360	360	360	360	360
T	532	532	532	532	532

Panel E: Own Constructed Anomalies

	ARMA11	Positive	Negative	WMP_TS_Tree	WMP_TS_FF30
Intercept	-0.00	0.03	0.03	0.06	0.06 **
	(-0.05)	(0.63)	(0.55)	(1.40)	(2.41)
WarFac	-0.67	-0.50	-0.58 ***	-0.78 ***	-0.09 ***
	(-1.53)	(-1.59)	(-2.59)	(-2.76)	(-2.68)
R^2	9	8	23	29	12
MAPE	0.35	0.35	0.32	0.30	0.34
N	128	128	128	128	128
T	532	532	532	532	532

Panel F: Own Constructed Nonlinear Portfolios

	ARMA11	Positive	Negative	WMP_TS_Tree	WMP_TS_FF30
Intercept	1.31 ***	1.14 ***	1.10 ***	1.29 ***	1.12 ***
	(4.27)	(3.28)	(3.59)	(4.17)	(4.51)
WarFac	-1.14 ***	-0.73 ***	-0.33 **	-0.63 ***	-0.08 ***
	(-3.05)	(-3.48)	(-2.42)	(-4.00)	(-3.36)
R^2	32	19	8	22	16
MAPE	0.09	0.10	0.10	0.09	0.10
N	2190	2190	2190	2190	2190
T	532	532	532	532	532

Table E.3
Choice of Seed Words and Topics

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta_{if}\lambda + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the factor exposure of portfolio i estimated via a time-series regression of portfolio return onto factor, and λ_f is the factor return premium. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D, own constructed anomalies in Panel E, and own constructed nonlinear portfolios in Panel F. Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively. Each column presents one specification of the sLDA model:

- (1) Base model with seed words as in Table A.1;
- (2) Added "conflict" and "tension" to *War* in (1);
- (3) Added "terrorism" and "terrorist" to *War* in (2);
- (4) Replaced *Pandemic* in (3) with "contagion, disease, epidemic, epidemiology, infection, outbreak, pandemic, public_health, quarantine, vaccination, vaccine, virus" and added *Natural Disaster* with "catastrophe, cyclone, destruction, drought, earthquake, flood, hurricane, landslide, mortality, natural_disaster, natural_hazard, storm, tornado, traumatic_exposure, tsunami, volcano, wildfire";
- (5) Replaced *War* in (4) with "army, battalion, battle, bomb, conflict, front_line, gun, military, munition, navy, officer, tension, terror, terrorism, terrorist, war, weapon";
- (6) Removed duplicates in seed words within and across topics in (5);
- (7) Estimated (1) with 50 unseeded topics; and
- (8) Used only one topic *War* with one seed word "war" with 50 unseeded topics.

Table E.3
Choice of Seed Words and Topics (Cont.)

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.18 ***	0.24 ***	0.23 ***	0.24 ***	0.24 ***	0.26 ***	0.21 ***	0.23 ***
	(2.97)	(4.34)	(3.87)	(4.15)	(4.21)	(4.86)	(3.55)	(3.52)
WarFac	-1.33 ***	-0.98 ***	-1.64 ***	-1.05 ***	-1.08 ***	-0.98 **	-0.83 ***	-1.03 **
	(-2.87)	(-2.58)	(-2.85)	(-2.76)	(-2.63)	(-2.42)	(-2.93)	(-2.34)
R^2	48	25	47	35	33	24	47	21
MAPE	0.26	0.32	0.26	0.30	0.30	0.32	0.26	0.33
N	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.76 ***	0.68 ***	0.73 ***	0.73 ***	0.70 ***	0.64 ***	0.65 ***	0.59 ***
	(3.79)	(3.49)	(3.48)	(3.83)	(3.78)	(3.16)	(3.00)	(2.63)
WarFac	-0.66 **	-0.43 *	-0.89 **	-0.48 *	-0.42 *	-0.39 *	-0.42 **	-0.37 **
	(-2.25)	(-1.78)	(-2.27)	(-1.91)	(-1.70)	(-1.68)	(-2.20)	(-2.47)
R^2	20	8	21	13	9	6	19	6
MAPE	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
N	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.16 ***	0.97 ***	0.98 ***	1.04 ***	0.98 ***	0.86 ***	0.96 ***	0.74 **
	(3.68)	(3.03)	(2.71)	(3.18)	(3.35)	(2.83)	(3.23)	(2.28)
WarFac	-1.26 ***	-0.88 ***	-1.71 ***	-0.94 ***	-0.71 ***	-0.74 **	-0.75 **	-0.73 **
	(-3.16)	(-2.85)	(-3.10)	(-3.11)	(-2.73)	(-2.40)	(-2.48)	(-2.01)
R^2	22	13	29	20	11	9	13	11
MAPE	0.18	0.19	0.17	0.18	0.19	0.19	0.19	0.19
N	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532

Table E.3
Choice of Seed Words and Topics (Cont.)

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.20	0.53	0.57	0.61	0.51	0.26	0.89	-0.03
	(1.19)	(0.74)	(0.66)	(0.87)	(0.90)	(0.47)	(0.93)	(-0.04)
WarFac	-3.32 ***	-2.10 ***	-3.85 ***	-2.01 ***	-1.57 **	-1.72 **	-2.46 ***	-1.90 **
	(-3.42)	(-2.70)	(-3.09)	(-3.17)	(-2.57)	(-2.13)	(-3.30)	(-2.01)
R^2	62	34	55	43	20	18	47	31
MAPE	0.44	0.58	0.46	0.53	0.65	0.66	0.53	0.62
N	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532

Panel E: Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.04	0.05	0.08 *	0.05	0.05	0.05	0.05	0.05
	(0.83)	(1.18)	(1.75)	(1.23)	(1.20)	(1.40)	(1.11)	(1.01)
WarFac	-1.02 **	-0.83 *	-1.54 **	-0.79 **	-0.85 **	-0.84 **	-0.66 **	-0.99 **
	(-2.12)	(-1.91)	(-2.29)	(-2.03)	(-2.01)	(-2.04)	(-2.04)	(-2.42)
R^2	19	11	22	13	11	9	16	14
MAPE	0.32	0.34	0.30	0.33	0.34	0.35	0.32	0.35
N	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532

Panel F: Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.18 ***	0.98 ***	1.04 ***	1.01 ***	0.99 ***	0.94 ***	1.07 ***	0.90 ***
	(3.60)	(3.48)	(3.15)	(3.49)	(3.49)	(3.62)	(3.19)	(3.68)
WarFac	-0.89 ***	-0.27	-1.28 ***	-0.37	-0.26	-0.13	-0.73 ***	-0.24
	(-3.64)	(-0.98)	(-3.88)	(-1.46)	(-1.01)	(-0.41)	(-3.86)	(-0.96)
R^2	16	2	22	5	2	0	20	2
MAPE	0.10	0.10	0.09	0.10	0.10	0.10	0.09	0.10
N	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532

F Protocol for Factor Identification

F.1 First Criterion: Correlation of factors with the Systematic Risk of Returns

If the factor mimicking portfolio of an observed factor represents a risk factor, it should be related to the systematic risk of returns. Following Pukthuanthong, Roll, and Subrahmanyam (2019) (hereafter, PRS), we test whether our War mimicking portfolio (WMP) is related to the cross-sectional covariance of asset returns. Specifically, we apply the asymptotic approach of Connor and Korajczyk (1988) (CK) to extract ten principal components from the equities return series. The principal components of the covariance matrix of returns represent the systematic part of the asset returns. We then compute canonical correlations between the ten CK principal components and the factor candidates and test the significance of these canonical correlations.

The implementation of the PRS approach comprises three steps. First, we collect a set of N equities for the factor candidates. The test assets should be from industries with enough heterogeneity to detect the underlying risk premium associated with factors. Second, we apply the CK approach to extract L principal components (PCs) from the return series. With T time-series units up to time t, we compute the $T \times T$ matrix $\Omega_t = \frac{1}{T}RR'$, where R is the return vector. CK demonstrate that for large N, analyzing the eigenvectors of Ω_t is asymptotically equivalent to factor analysis. The first L eigenvectors of Ω_t form the factor estimates. The cutoff point for $L < N$ is chosen so that the PCs explain at least 90% of the cumulative variance. Third, we collect a set of K factor candidates. Our study includes 14 factors, including *WMP*, five factors from FF6, three from M4, four from Q5, two from DHS, and one from the market.

Finally, from the second step above, we compute the canonical correlation between the factor candidates and the corresponding eigenvectors. First, we use the L eigenvectors from step 2 and the K factor candidates from step 3 and calculate the covariance matrix over a sample period t, V_t $(L + K \times L + K)$. We break out a submatrix from the covariance matrix V_t in each period, the cross-covariance matrix, denoted by C_t having K rows and L columns. The entry in the i^{th} row and j^{th} column is the covariance between factor candidate i and eigenvector j. We need to break out the covariance submatrix of the factor candidates, $V_{f,t}$

$(K \times K)$, and the covariance submatrix of the real eigenvectors, $V_{e,t}$ $(L \times L)$. We then can find two weighting column vectors, λ_t and κ_t, on the factor candidates and eigenvectors, respectively (λ_t has K rows, κ_t has L rows), that maximize the correlation between the two weighted vectors. The covariance between the weighted averages of factor candidates and eigenvectors is $\lambda_t' C_t \kappa_t$, and their correlation is

$$\rho = \frac{\lambda_t' C_t \kappa_t}{\sqrt{\lambda_t' V_{f,t} \lambda_t \kappa_t' V_{e,t} \kappa_t}} \tag{F.1}$$

We maximize the correlation across all choices of λ_t and κ_t. The maximum exists when the weight is $\lambda_t = V_{f,t}^{-1/2} h_t$, where h_t is the eigenvector corresponding to the maximum eigenvalue in the matrix $V_{f,t}^{-1/2} C_t V_{e,t}^{-1} C_t' V_{f,t}^{-1/2}$. κ_t is proportional to h_t.

We maximize the correlation again, subject to the constraint that the new vectors are orthogonal to the old ones, and so on. As a result, there are $min(L, K)$ pairs of orthogonal canonical variables sorted from the highest correlation to the smallest. We transform each correlation into a variable asymptotically distributed as Chi-Square under the null hypothesis that the actual correlation is zero. This provides a method of testing whether the factor candidates are conditionally related (on date t) to the covariance matrix of returns. Also, by examining the relative sizes of the weightings in λ_t, we can understand which factor candidates are more related to real return covariances. The intuition behind the canonical correlation approach is that the proper underlying drivers of returns are undoubtedly changes in perceptions about macroeconomic variables. But the factor candidates and the eigenvectors need not be isomorphic to a particular macro variable. Instead, each candidate or eigenvector is some linear combination of all the pertinent macro variables. This is the well-known "rotation" problem in principal components or factor analysis. The PRS criteria assert that some linear combinations of the factor candidates are strongly related to different linear combinations of the eigenvectors representing the actual factors. Canonical correlation is intended for this application. Any factor candidate that does not display a significant (canonical) correlation with its associated best linear combination of eigenvectors can be rejected as a viable factor. It is not significantly associated with the covariance matrix of asset returns.

We compute asymptotic PCs that represent the covariance matrix. We split the overall sample into five subsamples with ten years.[9] For each subsample, we use CK to extract PCs

[9]These five subsamples are 1967-1976, 1977-1986, 1987-1996, 1997-2006, and 2007-2016.

and retain the first ten PCs, which account for close to 90% of the cumulative eigenvalues or the total volatility in the covariance matrix, implying they capture most of the stock variations.

Next, we proceed to estimate the canonical correlations. We have several factor candidates and, thus, several pairs of canonical variates. We take the following steps to derive the significance levels of each factor candidate reported in the first row of Table F.1. First, for each of the ten canonical pairs, the eigenvector weights for the ten CK PCs are taken, and the weighted average CK PC or the canonical variate for the ten CK PCs that produced the canonical correlation for this particular pair is constructed.[10] Then a regression using each CK PC canonical variate as the dependent variable and the actual candidate factor values as independent variables are run over the sample months in each subperiod. The square root of the R-squared from the regression is the canonical correlation. After proper normalization, the coefficients for the regressions are equal to the eigenvector's weighting elements for the candidate factors. The t-statistic from the regression then gives the significance level of each candidate factor. With the ten pairs of canonical variates in each subperiod, and a canonical correlation for each one, we have 50 such regressions. The first row presents the mean t-statistic of all canonical correlations. The second row shows the mean t-statistic across cases when the canonical correlation is statistically significant. The last row shows the average number of significant canonical correlations across subperiods.

A risk factor *must* satisfy the necessary and sufficient conditions: (1) the risk factor is significantly related to any canonical variate in all decades, or it has a mean t-statistic exceeding the one-tailed 2.5% cutoff based on the Chi-squared value, and (2), in each subperiod, the risk factor has an average number of significant canonical correlations exceeding 2.50 (the bottom row of each panel). Researchers should test the augmented condition (the third condition) to ensure the robustness of the result. We leave it for other researchers to implement it. [11]

[10] There are $min(L, K)$ possible pairs. In our application, $L = 10$ and $K = 14$.

[11] Pukthuanthong, Roll, and Subrahmanyam (2019) require an average number of significant decade t-statistics exceeding 2.5 from 10 canonical variates (one-fourth of the total canonical variates). We use the same criteria as ten canonical variates (see the previous footnote). The reason to choose this value comes from Pukthuanthong, Roll, and Subrahmanyam (2019): "This is a conservative threshold to ensure we do not miss a true factor at our necessary condition stage. We focus on the significant canonical correlations rather than all canonical correlations because insignificant CCs imply that none of the factors matter, so using them would be over-fitting."

We examine this criterion for the WMP. As suggested in Pukthuanthong, Roll, and Subrahmanyam (2019), we use individual stocks to test the necessary condition. Our stock universe are stocks in the CRSP/Compustat merge file. Following standard practice, we exclude financial and utilities companies. We then split our sample from July 1972 to December 2016 into five subperiods: 1972-1976, 1977-1986, 1987-1996, 1997-2006, and 2007-2016.[12] We keep only stocks with non-missing returns during the five subperiods. As reported in Table F.1, WMP passes this criterion with an average t-stat of the significant canonical correlations (CC) of 2.26 and the average number of the significant CCs of 2.6, above the 2.5 threshold. Besides WMP, market (MKT) and momentum (MOM) are the other factors that pass this condition. MKT represents the most substantial pass. We conclude that our candidate global risk factors are WMP, MKT, and MOM.

F.2 Second Criterion: Risk Premium Estimation using WMP

The second criterion of the PRS protocol requires that the global risk factors or the factors that pass the necessary condition command a risk premium in the cross-section of asset returns. To perform this step, we re-run the standard two-pass regressions with the factors that pass the necessary condition. We report in Table F.2 that WMP prices all six sets of test assets after controlling for the other two risk factors that pass the first criterion of the protocol. MKT does not price any set of test assets with a positive risk premium, while MOM fails to price the 360 machine learning-based portfolios. We conclude that our *War* factor is a genuine risk factor.

[12]The sample period from July 1972 to December 2016 is when data on all factors are available.

Table F.1
Protocol Step 1: Correlation of WMP with the Systematic Risk of Returns

This table presents the results from the first step (necessary condition) of the protocol in Pukthuanthong, Roll, and Subrahmanyam (2019). Test assets are individual stocks in the CRSP/Compustat merge file, excluding financial and utilities firms. "*WMP*" is the *War* mimicking portfolio; "MKT, SMB, HML, RMW, CMA, MOM" are Fama and French (2018) six factors; "MKT, SMB, MGMT, PERF" are Stambaugh and Yuan (2017) mispricing factors; "PEAD" and "FIN" are Daniel, Hirshleifer, and Sun (2020) behavioral factors; and "R_ME, R_IA, R_ROE, R_EG" are Hou et al. (2021) Q5 factors. The sample is from July 1972 to December 2016.

	WMP	MKT	SMB	HML	RMW	CMA	MOM	MGMT	PERF	PEAD	FIN	R_ME	R_IA	R_ROE	R_EG
Avg. t	2.93	7.17	1.42	1.58	1.15	1.19	1.56	1.18	1.45	1.16	1.10	1.35	1.16	1.10	1.17
Avg. t (Sig. CC)	5.05	13.17	2.05	2.27	1.55	1.58	2.26	1.55	1.91	1.55	1.42	1.92	1.51	1.47	1.44
Period 1972:1976	5	3	1	3	2	3	1	2	2	3	1	1	2	0	1
Period 1977:1986	4	4	2	2	2	2	3	3	4	0	1	4	3	2	1
Period 1987:1996	3	3	4	3	1	3	3	4	0	4	3	3	1	0	3
Period 1997:2006	3	2	2	2	2	3	3	1	3	1	1	3	1	2	2
Period 2007:2016	4	4	3	4	2	2	4	2	3	2	3	2	3	3	2
# Sign. CC	3.80	3.20	2.40	2.80	1.80	2.60	2.80	2.40	2.40	2.00	1.80	2.60	2.00	1.40	1.80

Table F.2
Protocol Step 2: Two-Pass Regressions

This table presents the results from the second step (sufficient condition) of the protocol in Pukthuanthong, Roll, and Subrahmanyam (2019), i.e., second-pass cross-sectional regressions of average portfolio returns on factor betas:

$$\bar{R}^e_{it} = \lambda_0 + \beta'_{if}\lambda_f + e_i,$$

where $\bar{R}^e_{it}$ is the time-series average return of portfolio i, β_{if} is the vector of factor exposures of portfolio i estimated via a multivariate time-series regression of portfolio returns onto factors, and λ_f is the vector of factor risk premia. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) ("HXZ LS"), single-sorted portfolios from Hou, Xue, and Zhang (2020) ("HXZ Single"), single-sorted portfolios from Chen and Zimmermann (2022) ("CZ Single"), ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) ("ML-Based"), own constructed anomalies, and own constructed nonlinear portfolios. "*WMP*" is the *War* mimicking portfolio; and "MKT" and MOM" are from Fama and French (2018). Reported are monthly return premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percent, and MAPE is mean absolute pricing error in percent. N is the number of test portfolios, and T is the number of months. The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	HXZ LS	HXZ Single	CZ Single	ML-Based	Own Anomalies	Own Nonlinear
Intercept	0.10 ***	0.42 *	0.68 ***	-2.24 ***	-0.01	0.51 ***
	(3.72)	(1.91)	(4.80)	(-4.26)	(-0.35)	(2.81)
WMP	-3.62 ***	-1.83 ***	-1.55 ***	-3.21 ***	-3.24 ***	-1.23 ***
	(-5.70)	(-4.10)	(-4.86)	(-11.08)	(-7.01)	(-3.75)
MKT	0.38	0.14	-0.11	2.55 ***	0.72 **	0.26
	(1.12)	(0.48)	(-0.47)	(4.55)	(2.49)	(0.99)
SMB	-0.18	0.11	0.20	-0.57 ***	-0.12	-0.00
	(-1.06)	(0.73)	(1.43)	(-3.12)	(-0.77)	(-0.01)
HML	0.41 **	0.34 **	0.32 **	0.38 *	0.29 *	0.50 ***
	(2.52)	(2.24)	(2.14)	(1.84)	(1.84)	(2.96)
MOM	0.59 ***	0.56 ***	0.91 ***	1.24 ***	0.94 ***	0.79 ***
	(2.77)	(2.73)	(4.33)	(4.92)	(4.24)	(3.56)
PERF	0.59 **	0.60 ***	1.10 ***	3.20 ***	0.76 ***	0.99 ***
	(2.32)	(2.63)	(5.23)	(8.00)	(3.20)	(3.90)
R^2	68	51	46	74	41	56
MAPE	0.19	0.08	0.14	0.38	0.26	0.07
N	138	1372	904	360	128	2190
T	532	532	532	532	532	532

G The Result of the Three-Pass Test

Table G.1
Three-Pass Test

This table presents the results from the three-pass test of Giglio and Xiu (2021). λ is the factor return premium estimate (in percent); R^2_{TS} (in percent) is the R^2 of the time-series regression of each observed factor onto an optimal number of latent factors constructed from test asset returns (low values indicate large measurement errors); and p(weak) is the p-value of the Chi-squared test of whether the observed factor is a weak factor. Test assets include long-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, single-sorted portfolios from Chen and Zimmermann (2022) in Panel C, and ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2023) in Panel D, own constructed anomalies in Panel E, and own constructed nonlinear portfolios in Panel F. "WMP" is the is the mimicking portfolio of WarFac; "MKT, SMB, HML, RMW, CMA, MOM" are from Fama and French (2018); "MGMT, PERF" are from Stambaugh and Yuan (2017); "PEAD, FIN" are from Daniel, Hirshleifer, and Sun (2020); and "R_ME, R_IA, R_ROE, R_EG" are from Hou et al. (2021). The sample is from July 1972 to December 2016. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Long-Short Portfolios from Hou, Xue, and Zhang (2020)

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-0.48 **	-0.27 *	0.09	0.31 **	0.49 **	0.23 **	0.23 ***	0.35 ***	0.46 ***	0.12 **	0.52 ***	0.22 ***	0.24 **	0.23 ***
t	(-2.55)	(-1.82)	(0.68)	(2.35)	(2.51)	(1.99)	(2.72)	(2.89)	(2.85)	(2.01)	(3.19)	(2.79)	(2.08)	(3.12)
R^2_{TS}	15	42	70	73	87	74	67	74	64	33	76	61	77	53
p(weak)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel B: Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-0.17	-0.10	0.14	0.21 *	0.50 ***	0.09	0.15 *	0.16	0.29 **	0.08	0.27 *	0.14 *	0.16	0.09
t	(-1.13)	(-0.42)	(1.14)	(1.71)	(2.70)	(0.99)	(1.93)	(1.34)	(1.99)	(1.54)	(1.66)	(1.88)	(1.58)	(1.39)
R^2_{TS}	16	99	78	72	89	72	64	72	64	32	74	59	78	46
p(weak)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel C: Single-Sorted Portfolios from Chen and Zimmermann (2022)

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-1.12 ***	0.55 **	0.14	0.41 ***	0.48 ***	0.07	0.32 ***	0.50 ***	0.21	0.13 **	0.51 ***	0.29 ***	0.10	0.19 **
t	(-4.19)	(2.35)	(0.98)	(3.15)	(2.78)	(0.60)	(3.88)	(4.12)	(1.20)	(2.06)	(3.06)	(4.02)	(0.93)	(2.35)
R^2_{TS}	82	99	92	76	82	64	58	77	57	27	77	55	67	43
p(weak)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table G.1
Three-Pass Test (Cont.)

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2023)

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-3.11 ***	0.58	-0.10	0.17	0.99 ***	0.55 ***	0.01	0.13	0.73 ***	0.08	0.72 ***	0.09	0.68 ***	0.30 ***
t	(-10.19)	(1.57)	(-0.64)	(1.19)	(4.70)	(4.90)	(0.09)	(0.79)	(3.98)	(0.90)	(3.60)	(0.78)	(6.40)	(3.21)
R^2_{TS}	100	98	89	61	82	54	52	64	52	25	70	50	57	43
p(weak)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel E: Own Constructed Anomalies

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-0.37 **	-0.29 **	0.11	0.27 *	0.58 ***	-0.03	0.23 ***	0.28 **	0.26	0.14 **	0.29	0.20 **	0.04	0.10
t	(-2.19)	(-2.09)	(0.85)	(1.92)	(2.80)	(-0.28)	(2.74)	(2.31)	(1.58)	(2.18)	(1.61)	(2.49)	(0.33)	(1.49)
R^2_{TS}	14	33	58	73	82	56	65	69	60	30	76	61	61	45
p(weak)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel F: Own Constructed Nonlinear Portfolios

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-0.79 ***	0.06	0.20	0.28 ***	0.58 ***	0.17 *	0.19 ***	0.26 ***	0.36 **	0.07	0.41 ***	0.17 ***	0.18 *	0.11 *
t	(-3.22)	(0.29)	(1.51)	(2.88)	(3.21)	(1.74)	(3.04)	(2.79)	(2.33)	(1.39)	(2.76)	(3.09)	(1.68)	(1.80)
R^2_{TS}	80	92	67	53	78	52	50	65	50	21	68	49	54	38
p(weak)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

H Details on Portfolio Construction

H.1 128 Own Constructed Anomalies

In this subsection, we report our constructed portfolios' descriptive statistics based on Hou, Xue, and Zhang (2020).

Table H.1
128 Own Constructed Anomalies

This table presents descriptive statistics of the portfolios we apply in our cross-sectional tests. Our sample period is from 1967 to 2016. The candidate factors are constructed similarly to Hou, Xue, and Zhang (2020). We use the same screening criteria, delisting procedure, and period similar to what they do. The first column presents the identification numbers and names of the candidate factors according to their papers. The last four columns present the number of observations, the mean of candidate factors, t-stat testing the mean is statistically different from zero, and the standard deviation of candidate factors. All candidate factors are based on one-month calculation, and these portfolios are equal-weighted returns. ***, **, and * present 1%, 5%, and 10% significance level.

Candidate factors	# obs	mean	t-stat	std.dev
A. Momentum				
A.1.1 Standardized unexpected earnings	534	0.01	4.97***	0.04
A.1.2 Cumulative abnormal returns around earnings announcement dates	521	0.02	8.57***	0.04
A.1.4 Price momentum, prior 6-month returns	534	0.01	3.13***	0.08
A.1.5 Price momentum, prior 11-month returns	534	0.01	4.24***	0.08
A.1.6 Industry momentum	534	0.57	2.23**	5.90
A.1.7 Revenue surprises	534	0.00	1.37	0.04
A.1.10 The number of quarters with consecutive earnings increase	533	0.00	1.76*	0.07
A.1.11 52-week high	529	-0.00	-0.18	0.07
A.1.12 Residual momentum, prior 6-month returns	534	0.00	1.40	0.06
A.1.13 Residual momentum, prior 11-month returns	534	0.01	3.89***	0.06
B. Value versus growth				
B.2.1 Book-to-market equity	534	0.00	2.17**	0.05
B.2.2 Book-to-June-end market equity	534	0.00	2.33**	0.05
B.2.3 Quarterly book-to-market equity	534	0.02	6.88***	0.06
B.2.6 Assets-to-market	534	0.00	2.07**	0.06
B.2.8 Reversal.	534	-0.00	-1.81*	0.06
B.2.9 Earnings-to-price	534	0.00	0.93	0.06
B.2.12 Cash flow-to-price	534	0.00	0.12	0.05
B.2.14 Dividend yield	534	0.00	1.01	0.04
B.2.16 Payout yield	529	0.00	2.59**	0.05
B.2.16 Net payout yield	529	0.00	2.51**	0.05
B.2.18 5-year sales growth rank	534	-0.00	-0.72	0.04
B.2.19 Sales growth	534	-0.00	-1.13	0.04
B.2.20 Enterprise multiple	534	-0.00	-2.00**	0.06
B.2.22 Sales-to-price	534	0.01	2.68**	0.06
B.2.26 Intangible return	534	-0.01	-4.88***	0.04
B.2.30 Equity duration	534	-0.01	-3.18***	0.06
C. Investment				
C.3.1 Abnormal corporate investment	534	-0.00	-2.11**	0.03
C.3.2 Investment-to-assets	534	0.00	4.03***	0.01
C.3.3 Quarterly investment-to-assets	522	-0.00	-0.67	0.03
C.3.4 Changes in PPE and inventory-to-assets	534	-0.00	-3.01***	0.03
C.3.5 Noa and dNoa, (changes in) net operating assets	534	-0.01	-4.06***	0.03
C.3.6 Changes in long-term net operating assets.	534	-0.00	-3.00**	0.03
C.3.7 Investment growth	534	-0.00	-3.48***	0.03
C.3.8 2-year investment growth	534	-0.00	-1.93**	0.03
C.3.9 3-year investment growth	534	-0.00	-1.38	0.03
C.3.10 Net stock issues	534	-0.00	-3.55***	0.03

C.3.11 Percentage change in investment relative to industry	534	-0.00	-2.34**	0.03
C.3.12 Composite equity issuance	534	-0.00	-0.82	0.04
C.3.13 Composite debt issuance	534	-0.00	-0.42	0.04
C.3.14 Inventory growth	534	-0.00	-2.06**	0.03
C.3.15 Inventory changes	534	-0.00	-2.92***	0.03
C.3.16 Operating accruals	534	-0.00	-2.17**	0.03
C.3.17 Total accruals	534	-0.00	-1.96*	0.04
C.3.18 Changes in net noncash working capital, in current operating assets, and in current operating liabilities	534	-0.00	-1.12	0.04
C.3.19 Changes in noncurrent operating assets	534	-0.00	-3.42***	0.03
C.3.19 Changes in noncurrent operating liabilities	534	-0.00	-0.87	0.03
C.3.19 Changes in net noncurrent operating assets	534	-0.00	-3.34***	0.03
C.3.20 Changes in book equity	534	-0.00	-0.28	0.05
C.3.20 Changes in net financial assets	534	0.00	2.04**	0.03
C.3.20 Changes in financial liabilities	534	-0.00	-1.34	0.02
C.3.20 Changes in in long-term investments	534	-0.00	-1.36	0.03
C.3.20 Changes in short-term investments	534	0.00	0.39	0.02
C.3.21 Discretionary accruals computed from Nasdaq Index	516	-0.00	-1.94*	0.04
C.3.21 Discretionary accruals computed from NYSE and Amex	534	-0.00	-1.41	0.03
C.3.22 Percent operating accruals	534	-0.00	-3.06***	0.03
C.3.23 Percent total accruals	534	-0.00	-1.42	0.03
C.3.24 Percent discretionary accruals	534	-0.00	-2.31**	0.03
C.3.25 Net debt financing	528	-0.00	-1.94*	0.03
C.3.25 Net equity financing	528	-0.00	-0.80	0.05
C.3.25 Net external financing	528	-0.00	-1.83*	0.04
D. Profitability				
D.4.1 Return on equity	534	0.02	8.13***	0.05
D.4.2 4-quarter change in return on equity	528	0.00	2.71**	0.04
D.4.3 Roa1, Roa6, and Return on assets	534	0.01	7.40***	0.05
D.4.4 4-quarter change in return on assets.	522	0.00	2.81***	0.04
D.4.5 Assets turnover	534	0.00	0.54	0.04
D.4.5 Profit margin	534	0.00	0.24	0.05
D.4.5 Return on net operating assets	534	0.00	0.48	0.04
D.4.6 Capital turnover	534	0.00	0.89	0.04
D.4.7 Quarterly assets turnover	534	0.00	2.18**	0.04
D.4.7 Quarterly profit margin	534	0.00	2.43**	0.05
D.4.7 Quarterly return on net operating assets	486	0.00	2.37**	0.04
D.4.8 Quarterly capital turnover	534	0.01	3.63***	0.04
D.4.9 Gross profits-to-assets.	534	0.00	1.90*	0.03
D.4.10 Gross profits-to-lagged assets	534	0.00	0.20	0.04
D.4.11 Quarterly gross profits-to-lagged assets	486	0.00	3.14***	0.03

D.4.12 Operating profits to equity	534	0.00	1.14	0.05
D.4.13 Operating profits-to-lagged equity	534	0.00	0.40	0.04
D.4.14 Quarterly operating profits-to-lagged equity	534	0.01	3.39***	0.06
D.4.15 Operating profits-to-assets	534	0.00	2.04**	0.04
D.4.16 Operating profits-to-lagged assets	534	0.00	1.41	0.04
D.4.17 Quarterly operating profits-to-lagged assets	486	0.01	4.30***	0.04
D.4.18 Cash-based operating profitability	534	0.01	3.53***	0.04
D.4.19 Cash-based operating profits-to-lagged asset	534	0.00	2.76***	0.04
D.4.20 Quarterly cash-based operating profits-to-lagged assets	486	0.01	4.32***	0.04
D.4.21 Fundamental score.	528	0.00	1.70*	0.03
D.4.24 Ohlsons O-score	534	0.00	0.32	0.04
D.4.25 Quarterly O-score	486	-0.00	-1.26	0.03
D.4.26 Altmans Z-score	534	-0.00	-2.01**	0.05
D.4.27 Quarterly Z-score	486	-0.00	-2.07**	0.05
D.4.29 Taxable income-to-book income.	534	0.00	0.24	0.03
D.4.30 Quarterly taxable income-to-book income	534	0.00	0.58	0.04
D.4.31 Growth score	348	0.00	1.08	0.08
D.4.32 Book leverage	534	0.00	0.44	0.04
D.4.33 Quarterly book leverage	534	0.00	0.14	0.04
E. Intangibles				
E.5.1 Industry adjusted organizational capital-to-assets	534	0.00	0.35	0.04
E.5.2 Advertising expense-to-market	534	0.00	0.17	0.03
E.5.3 Growth in advertising expense.	534	0.00	3.38***	0.01
E.5.4 R&D expense-to-market	534	-0.00	-0.93	0.04
E.5.8 Operating leverage	534	0.00	0.44	0.03
E.5.9 Olq1, Olq6, and Olq12, quarterly operating leverage	522	0.00	2.55**	0.03
E.5.10 Hiring rate	534	0.00	2.94***	0.01
E.5.11 R&D capital-to-assets	534	0.00	0.25	0.04
E.5.12 Bca, brand capital-to-assets.	516	0.01	2.05**	0.07
E.5.17 Ha, industry concentration (assets)	534	-0.00	-1.25	0.05
E.5.17 He, industry concentration (book equity)	534	-0.00	-1.10	0.04
E.5.17 Hs, industry concentration (sales)	534	-0.00	-1.39	0.04
E.5.19 D1, price delay	534	0.00	0.98	0.04
E.5.19 D2, price delay	534	0.00	-0.11	0.02
E.5.19 D3, price delay	534	0.00	-0.41	0.02
E.5.20 % change in sales minus % change in inventory	534	0.00	0.44	0.00
E.5.21 % change in sales minus % change in accounts receivable	534	0.00	1.08	0.01
E.5.22 % change in gross margin minus % change in sales	534	0.00	2.28**	0.01
E.5.23 % change in sales minus % change in SG&A	534	0.00	1.43	0.00
E.5.24 Effective tax rate	534	0.00	1.43	0.00

E.5.25 Labor force efficiency	534	0.00	1.17	0.00
E.5.26 Analysts coverage	485	-0.00	-0.43	0.03
E.5.27 Tangibility	534	-0.00	-0.83	0.03
E.5.28 Quarterly tangibility.	534	0.00	0.16	0.03
E.5.29 Industry-adjusted real estate ratio	534	0.00	0.47	0.04
E.5.30 Financial constraints (the Kaplan-Zingales index)	534	0.00	1.52	0.03
E.5.32 Financial constraints (the Whited-Wu index)	534	0.00	0.12	0.03
E.5.33 Wwq1, Wwq6, and Wwq12, the quarterly Whited-Wu index	534	0.00	0.33	0.04
E.5.34 Secured debt-to-total debt	534	-0.00	-0.65	0.03
E.5.35 Convertible debt-to-total debt	534	0.00	0.83	0.04
E.5.37 Cta1, Cta6, and Cta12, cash-to-assets	534	0.00	1.08	0.04
E.5.41 Earnings persistence	534	-0.00	-0.66	0.03
E.5.41 Earnings predictability	534	-0.00	-2.16**	0.04
E.5.42 Earnings smoothness	534	-0.00	-1.01	0.03
E.5.44 Earnings conservatism	534	-0.00	-1.48	0.03
E.5.44 Earnings timeliness	534	0.00	0.10	0.03
E.5.44 Earnings conservatism	534	0.00	0.76	0.02
E.5.44 Earnings timeliness	534	0.00	1.11	0.02
E.5.45 FRM, Pension plan funding rate	534	0.00	0.98	0.02
E.5.45 FRA, Pension plan funding rate	534	-0.00	-1.70*	0.03
E.5.46 Ala, asset liquidity	486	0.00	-0.12	0.04
E.5.46 Alm, asset liquidity	486	0.00	1.69	0.05
E.5.51 Average returns Ra1	534	0.00	7.55***	0.00
E. 5.51 Average returns Ra[2,5]	534	0.00	3.60***	0.00
E.5.51 Average returns Ra[6,10]	534	0.00	3.55***	0.00
E.5.51 Average returns Rn1	534	0.00	4.95***	0.01
E. 5.51 Average returns Rn[2,5]	534	0.00	3.35***	0.01
E.5.51 Average returns Rn[6,10]	534	0.00	3.14***	0.01
E.5.51 Average returns Rn[16,20]	534	0.00	1.15	0.04
F. Trading frictions				
F.6.1 Me, market equity	534	-0.00	-0.48	0.05
F.6.2 Ivff1, Ivff6, and Ivff12, idiosyncratic volatility per the Fama and French (1993) 3-factor model	534	-0.01	-2.54**	0.09
F.6.3 Iv, idiosyncratic volatility	534	-0.01	-3.41***	0.08
F.6.5 Ivq1, Ivq6, and Ivq12, idiosyncratic volatility	534	-0.01	-3.34***	0.08
F.6.6 Tv1, Tv6, and Tv12, total volatility	534	-0.01	-3.43***	0.09
F.6.8 beta_1, beta_6, and beta_12, market beta	534	0.00	-0.12	0.08
F.6.9 beta_FP1, beta_FP6, and beta_FP12, the Frazzini-Pedersen beta	534	-0.01	-1.53	0.10
F.6.10 beta_D1, beta_D6, and beta_D12, the Dimson beta	533	-0.00	-0.51	0.06
F.6.11 Tur1, Tur6, and Tur12, share turnover	534	-0.00	-0.82	0.06
F.6.12 Cvt1, Cvt6, and Cvt12, coefficient of variation of share turnover	533	0.00	-0.11	0.03

F.6.13 Dtv1, Dtv6, and Dtv12, dollar trading volume	533	-0.00	-0.60	0.03
F.6.14 Cvd1, Cvd6, and Cvd12, coefficient of variation of dollar trading volume.	533	0.00	0.37	0.03
F.6.15 Pps1, Pps6, and Pps12, share price	534	0.00	0.13	0.08
F.6.16 Ami1, Ami6, and Ami12, absolute return-to-volume	533	-0.00	-0.40	0.05
F.6.17 Lm11, Lm16, Lm112, turnover-adjusted number of zero daily volume	533	0.00	-0.01	0.06
F.6.17. Lm121, Lm126, Lm1212, turnover-adjusted number of zero daily volume	533	0.00	0.70	0.06
F.6.17, Lm61, Lm66, Lm612, turnover-adjusted number of zero daily volume	533	0.00	0.71	0.06
F.6.18 Mdr1, Mdr6, and Mdr12, maximum daily return	534	-0.01	-2.59**	0.07
F.6.20 Isc1, Isc6, and Isc12, idiosyncratic skewness per the CAPM	534	0.00	2.25**	0.03
F.6.21 Isff1, Isff6, and Isff12, idiosyncratic skewness per the Fama and French	534	0.00	2.76***	0.03
F.6.23 Cs1, Cs6, and Cs12, coskewness	534	-0.00	-0.81	0.03
F.6.25 beta_lcc1, beta_lcc6, beta_lcc12, liquidity betas illiquidity-illiquidity	533	0.03	9.20***	0.06
F.6.25 beta_lcr1, beta_lcr6, beta_lcr12, liquidity betas (illiquidity-return)	533	0.00	0.44	0.04
F.6.25 beta_lrc1, beta_lrc6, beta_lrc12, liquidity betas return illiquidity	533	-0.00	-1.63	0.05
F.6.25 beta_net1, beta_net6, and beta_net12, liquidity betas (net)	533	0.01	1.86*	0.08
F.6.25 beta_ret1, beta_ret6, and beta_ret12, liquidity betas (return-return)	533	0.01	1.89*	0.08
F.6.26 Short-term reversal	533	0.00	1.31	0.05
F.6.27 beta_-1, beta_-6, and beta_-12, downside beta	533	-0.00	-0.63	0.07
F.6.31 beta_PS1, beta_PS6, and beta_PS12, the Pastor-Stambaugh beta	534	0.00	0.30	0.04

H.2 2190 Own Constructed Nonlinear Portfolios

We construct 2190 portfolios based on the nonlinear functions of nine characteristics that Freyberger, Neuhierl, and Weber (2020) find significantly explain cross-sectional stock returns. We call them nonlinear portfolios or factors. We apply the following procedure to construct these portfolios. As an indication, we use three characteristics (X1, X2, and X3) as an example.

1. We generate the following characteristics up to polynomials of degree 3, including

X1, X2, X3, X1X2, X1X3, X2X3, X1X2X3, X1X1X3, X1X1X2, X1X2X2, X2X2X3, X1X3X3, X2X3X3, X1^2, X2^2, X3^2, X1^3, X2^3, X3^3.

We alleviate multicollinearity concerns among these characteristics by orthogonalizing each characteristic using a residual from regressing characteristics on its linear and nonlinear components. For instance, we use the residual of regressing X1X2X2 on X1, X2, X1X2, and X2X2 instead of using X1X2X2 directly, or the residual of regressing X1X2 on X1 and X2, instead of using X1X2. Generally, we use X^3-C1*X-C2*X^2 where C1 and C2 are estimated coefficients from regressing X^3 on X and X^2, respectively to eliminate the impact of both X and X^2 from X^3, or X^2-C2*X1, which is a residual from regressing X^2 on X1.

There are two benefits of using residuals. First, the residual methods can remove all the possible correlations between X and X^2. Second, if X's have a different sign (for instance, X1=-2, X2 = 0, and X3=1), $X1 < X2 < X3$ but $X2^2 < X3^2 < X1^2$ and $X1^3 < X2^3 < X3^3$. The relation is not monotonic if X1 to Xn have different signs. Using residuals will take care of this regardless of the sign.

2. We standardize characteristics firm by firm each time to avoid look-ahead bias and prevent the mis-ranking issue.
3. We sort stocks into deciles based on the transformed characteristics above, calculate the average returns next period by group, and assign them to the corresponding characteristics and decile (for example, X1_1).
4. We create long-short portfolios, i.e., ten minus one for each transformed characteristic.
5. We use 360 ML-based nonlinear portfolios developed by Bryzgalova, Pelger, and Zhu (2023) (see Appendix H.3 for the list and description).[13] These portfolios can capture the higher dimensional nonlinear information from characteristics.

[13]We thank Marcus Pelger for generously providing us with the portfolio data.

Table H.2
2190 Own Constructed Nonlinear Portfolios

This table presents nine characteristics selected by Freyberger, Neuhierl, and Weber (2020) and 2190 nonlinear characteristic-sorted decile portfolios constructed based on 219 characteristics. See Section H.2 for the detailed construction. The nine characteristics are *agr* defined as annual percent change in total assets from Cooper and Priestley (2009), *chcsho* or annual percent change in shares outstanding from Pontiff and Woodgate (2008), *mom1m* defined as 1-month cumulative return from Jegadeesh and Titman (1993), *mom12m* defined as 11-month cumulative returns ending one month before month end from Jegadeesh (1990), *mom36m* defined as cumulative returns from months t-36 to t-13, *operprof* or revenue minus cost of goods sold, SG&A expense, and interest expense divided by lagged common shareholders' equity (Fama and French, 2015), *mve* or natural log of market capitalization at the end of month t-1 from Banz (1981), *retvol* or standard deviation of daily returns from month t-1 from Ang et al. (2006), and *turn* or the average monthly trading volume for most recent 3 months scaled by number of shares outstanding in current month from Datar, Naik, and Radcliffe (1998).

Portfolio name	ID	Portfolio name	ID	Portfolio name	ID	Portfolio name	ID	Portfolio name	ID
agr_agr	X8	agr_mom12m_retvol	X52	mom12m_retvol_retvol	X97	chcsho_operprof_turn	X143	chcsho_mom36m_operprof	X189
agr_chcsho	X9	agr_mom12m_turn	X53	mom12m_retvol_turn	X98	mom12m_mom12m_operprof	X144	chcsho_mom36m_retvol	X190
agr_mom12m	X10	agr_mom1m_mom1m	X54	mom12m_turn_turn	X99	mom12m_mom1m_operprof	X145	chcsho_mom36m_turn	X191
agr_mom1m	X11	agr_mom1m_mve	X55	mom1m_mom1m_mom1m	X100	mom12m_mve_operprof	X146	mom2m_mom2m_mom36m	X192
agr_mve	X12	agr_mom1m_retvol	X56	mom1m_mom1m_mve	X101	mom12m_operprof_operprof	X147	mom12m_mom1m_mom36m	X193
agr_retvol	X13	agr_mom1m_turn	X57	mom1m_mom1m_retvol	X102	mom12m_operprof_retvol	X148	mom12m_mom36m_mom36m	X194
agr_turn	X14	agr_mve_mve	X58	mom1m_mom1m_turn	X103	mom12m_operprof_turn	X149	mom12m_mom36m_mve	X195
chcsho_chcsho	X15	agr_mve_retvol	X59	mom1m_mve_mve	X104	mom1m_mom1m_operprof	X150	mom12m_mom36m_operprof	X196
chcsho_mom12m	X16	agr_mve_turn	X60	mom1m_mve_retvol	X105	mom1m_mve_operprof	X151	mom12m_mom36m_retvol	X197
chcsho_mom1m	X17	agr_retvol_retvol	X61	mom1m_mve_turn	X106	mom1m_operprof_operprof	X152	mom12m_mom36m_turn	X198
chcsho_mve	X18	agr_retvol_turn	X62	mom1m_retvol_retvol	X107	mom1m_operprof_retvol	X153	mom1m_mom1m_mom36m	X199
chcsho_retvol	X19	agr_turn_turn	X63	mom1m_retvol_turn	X108	mom1m_operprof_turn	X154	mom1m_mom36m_mom36m	X200
chcsho_turn	X20	chcsho_chcsho_chcsho	X64	mom1m_turn_turn	X109	mve_mve_operprof	X155	mom1m_mom36m_mve	X201
mom12m_mom12m	X21	chcsho_chcsho_mom12m	X65	mve_mve_mve	X110	mve_operprof_operprof	X156	mom1m_mom36m_operprof	X202
mom12m_mom1m	X22	chcsho_chcsho_mom1m	X66	mve_mve_retvol	X111	mve_operprof_retvol	X157	mom1m_mom36m_retvol	X203
mom12m_mve	X23	chcsho_chcsho_mve	X67	mve_mve_turn	X112	mve_operprof_turn	X158	mom1m_mom36m_turn	X204
mom12m_retvol	X24	chcsho_chcsho_retvol	X68	mve_retvol_retvol	X113	operprof_operprof_operprof	X159	mom36m_mom36m_mom36m	X205
mom12m_turn	X25	chcsho_chcsho_turn	X69	mve_retvol_turn	X114	operprof_operprof_retvol	X160	mom36m_mom36m_mve	X206
mom1m_mom1m	X26	chcsho_mom12m_mom12m	X70	mve_turn_turn	X115	operprof_operprof_turn	X161	mom36m_mom36m_operprof	X207
mom1m_mve	X27	chcsho_mom12m_mom1m	X71	retvol_retvol_retvol	X116	operprof_retvol_retvol	X162	mom36m_mom36m_retvol	X208
mom1m_retvol	X28	chcsho_mom12m_mve	X72	retvol_retvol_turn	X117	operprof_retvol_turn	X163	mom36m_mom36m_turn	X209
mom1m_turn	X29	chcsho_mom12m_retvol	X73	retvol_turn_turn	X118	operprof_turn_turn	X164	mom36m_mve_mve	X210
mve_mve	X30	chcsho_mom12m_turn	X74	turn_turn_turn	X119	agr_mom36m	X166	mom36m_mve_operprof	X211
mve_retvol	X31	chcsho_mom1m_mom1m	X75	agr_operprof	X121	chcsho_mom36m	X167	mom36m_mve_retvol	X212
mve_turn	X32	chcsho_mom1m_mve	X76	chcsho_operprof	X122	mom12m_mom36m	X168	mom36m_mve_turn	X213
retvol_retvol	X33	chcsho_mom1m_retvol	X77	mom12m_operprof	X123	mom1m_mom36m	X169	mom36m_operprof_operprof	X214
retvol_turn	X34	chcsho_mom1m_turn	X78	mom1m_operprof	X124	mom36m_mom36m	X170	mom36m_operprof_retvol	X215
turn_turn	X35	chcsho_mve_mve	X79	mve_operprof	X125	mom36m_mve	X171	mom36m_operprof_turn	X216
agr_agr_agr	X36	chcsho_mve_retvol	X80	operprof_operprof	X126	mom36m_operprof	X172	mom36m_retvol_retvol	X217
agr_agr_chcsho	X37	chcsho_mve_turn	X81	operprof_retvol	X127	mom36m_retvol	X173	mom36m_retvol_turn	X218
agr_agr_mom12m	X38	chcsho_retvol_retvol	X82	operprof_turn	X128	mom36m_turn	X174	mom36m_turn_turn	X219
agr_agr_mom1m	X39	chcsho_retvol_turn	X83	agr_agr_operprof	X129	agr_agr_mom36m	X175		
agr_agr_mve	X40	chcsho_turn_turn	X84	agr_chcsho_operprof	X130	agr_chcsho_mom36m	X176		
agr_agr_retvol	X41	mom12m_mom12m_mom12m	X85	agr_mom12m_operprof	X131	agr_mom12m_mom36m	X177		
agr_agr_turn	X42	mom12m_mom12m_mom1m	X86	agr_mom1m_operprof	X132	agr_mom1m_mom36m	X178		
agr_chcsho_chcsho	X43	mom12m_mom12m_mve	X87	agr_mve_operprof	X133	agr_mom36m_mom36m	X179		
agr_chcsho_mom12m	X44	mom12m_mom12m_retvol	X88	agr_operprof_operprof	X134	agr_mom36m_mve	X180		
agr_chcsho_mom1m	X45	mom12m_mom12m_turn	X89	agr_operprof_retvol	X135	agr_mom36m_operprof	X181		
agr_chcsho_mve	X46	mom12m_mom1m_mom1m	X90	agr_operprof_turn	X136	agr_mom36m_retvol	X182		
agr_chcsho_retvol	X47	mom12m_mom1m_mve	X91	chcsho_chcsho_operprof	X137	agr_mom36m_turn	X183		
agr_chcsho_turn	X48	mom12m_mom1m_retvol	X92	chcsho_mom12m_operprof	X138	chcsho_chcsho_mom36m	X184		
agr_mom12m_mom12m	X49	mom12m_mom1m_turn	X93	chcsho_mom1m_operprof	X139	chcsho_mom12m_mom36m	X185		
agr_mom12m_mom1m	X50	mom12m_mve_mve	X94	chcsho_mve_operprof	X140	chcsho_mom1m_mom36m	X186		
agr_mom12m_mve	X51	mom12m_mve_retvol	X95	chcsho_operprof_operprof	X141	chcsho_mom36m_mom36m	X187		
		mom12m_mve_turn	X96	chcsho_operprof_retvol	X142	chcsho_mom36m_mve	X188		

H.3 360 ML-based Nonlinear Portfolios

This subsection shows 360 ML-based nonlinear portfolios for each characteristic group containing ten decile portfolios. See Bryzgalova, Pelger, and Zhu (2023) for the detailed construction and the following tables for variable descriptions.

Table H.3
360 ML-based Nonlinear Characteristics Groups

LME_AC_IdioVol
LME_AC_Lturnover
LME_BEME_AC
LME_BEME_IdioVol
LME_BEME_Investment
LME_BEME_LT_Rev
LME_BEME_Lturnover
LME_BEME_OP
LME_BEME_r12_2
LME_BEME_ST_Rev
LME_IdioVol_Lturnover
LME_Investment_AC
LME_Investment_Idiovol
LME_Investment_LT_Rev
LME_investment_Lturnover
LME_Investment_ST_Rev
LME_LT_Rev_AC
LME_LT_Rev_IdioVol
LME_LT_Rev_Lturnover
LME_OP_AC
LME_OP_IdioVol
LME_OP_Investment
LME_OP_LT_Rev
LME_OP_Lturnover
LME_OP_ST_Rev
LME_r12_2_AC
LME_r12_2_IdioVol
LME_r12_2_Investment
LME_r12_2_LT_Rev
LME_r12_2_Lturnover
LME_r12_2_OP
LME_r12_2_ST_Rev
LME_ST_REV_AC
LME_ST_Rev_IdioVol
LME_ST_Rev_LT_Rev

Table H.4
10 ML-Based Characteristics

Symbol	Names	Description	References
AC	Accrual	Change in operating working capital per split-adjusted share from the scal year	Sloan (1996)
BEME	Book-to-Market ratio	Book equity is shareholder equity (SH) plus deferred taxes and investment tax credit (TXDITC), minus preferred stock (PS). SH is shareholders equity (SEQ). If missing, SH is the sum of common equity (CEQ) and preferred stock (PS). If missing, SH is the difference between total assets (AT) and total liabilities (LT). Depending on availability, we use the redemption (item PSTKRV), liquidating (item PSTKL), or per value (item PSTK) for PS. The market value of equity (PRC*SHROUT) is as of December t-1.	Basu (1983), Fama and French (1992)
IdioVol	Idiosyncratic volatility	Standard deviation of the residuals from a regression of excess returns on the Fama and French three-factor model	Ang et al. (2006)
Investment	Investment	Change in total assets (AT) from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets	Fama and French (2015)
LME	Size	Total market capitalization at the end of the previous month defined as price times shares outstanding	Banz (1981), Fama and French (1992)
LT_Rev	Long-term reversal	Cumulative return from 60 months before the return prediction to 13 months before	De Bondt and Thaler (1985)
LTurnover	Turnover	Last month's volume (VOL) over shares outstanding (SHROUT)	Datar, Naik, and Radcliffe (1998)
OP	Operating profitability	Annual revenues (REVT) minus cost of goods sold (COGS), interest expense (TIE), and selling, general, and administrative expenses (XSGA) divided by book equity (defined in BEME)	Fama and French (2015)
r12_2	Momentum	Return for the first 12 months except for the first month	Jegadeesh (1990)
ST_Rev	Short-term reversal	Prior month return	Jegadeesh (1990)