NBER WORKING PAPER SERIES

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Working Paper 31348
http://www.nber.org/papers/w31348

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2023

We do not have any finance research support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 31348
June 2023
JEL No. G0,G02,G1,G10,G11,G4,G41

ABSTRACT

A war-related factor model derived from textual analysis of media news reports explains the cross section of expected asset 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

Rare disaster risk has been proposed as a possible explanation for long-standing asset-pricing puzzles, such as the equity premium and volatility puzzles. This explanation has received increased attention in recent years. Studies have attempted to justify the equity premium as a rational compensation for disaster risk (Rietz 1988). Barro (2006) extends this approach to account for the observed equity premium using realistic risk aversion parameters.

Gabaix (2012), Gourio (2008), and Wachter (2013) model time-varying disaster risk as a key mechanism driving time-varying asset expected returns to help explain several puzzles in asset markets, such as the excess volatility puzzle, the predictability of equity market returns by price dividend ratios, the cross-sectional predictability of stock returns, and the term spread puzzle. The authors argue time-varying probability or severity of rare disasters can significantly affect asset prices and returns and that these effects can help explain observed anomalies that are otherwise difficult to reconcile with standard financial models.

The theory that high expected market equity returns derive from rare disaster risks suggests a natural cross-sectional implication: that an asset such as gold that provides high returns when a rare disaster occurs is a good hedge and, thus, should have low expected returns. For example, in the ICAPM Merton (1973), state variables that capture future investment opportunities can predict returns incrementally to CAPM beta.

A behavioral perspective suggests a similar implication for a different reason: overweighting of the prospect of an extreme disaster. For example, investors may overestimate the probability of disaster because of its high salience. Alternatively, investors may overweight low probabilities, as in cumulative prospect theory, 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 test here whether assets with high exposure to disaster risk tend to have lower expected returns. Our focus is on war-related disaster risk. This emphasis aligns with Barro (2006) and Hirshleifer, Mai, and Pukthuanthong (2023). 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 (2023) 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. Our study examines whether the war risk measure of Hirshleifer, Mai, and Pukthuanthong (2023) can be applied to predict 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).

In this paper, rather than realized war events, we focus on variation in investor attention to war risk as reflected in news media. Textual news material contains information about current expectations (Gentzkow and Shapiro 2010; Mullainathan and Shleifer 2005). We test for the effect of war perceptions on the cross section of expected stock returns. 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.

Specifically, our approach is based on Hirshleifer, Mai, and Pukthuanthong (2023), who construct a war risk topic (hereafter, *War*) from *The New York Times* (*NYT*) since 1871. They apply a novel 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 the information available only then. This allows them to avoid look-ahead bias, a core issue for testing asset return predictability. In addition, the technique allows them to adjust their semantic changes over time.

We construct a *War* factor (hereafter, WarFac) as a shock to the news-based *War* index and its traded version by forming a factor mimicking portfolio. We find that the *War* factor 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.

In cross-sectional tests, the set of test assets is crucial (Giglio, Xiu, and Zhang 2021). A low dimensionality of test assets favors the factors constructed by corresponding characteristics (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] 1372 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 (2020),

[5] our own constructed 128 long-short portfolios, and

[6] our own constructed 2190 nonlinear portfolios.

We find that WarFac exhibits a stable and statistically significant return premium when applied to diverse cross sections of test assets. It is noteworthy that WarFac excels in pricing returns of the machine learning-based nonlinear portfolios of Bryzgalova, Pelger, and Zhu (2020) (hereafter, ML-based nonlinear portfolios). Using these ML-based nonlinear portfolios as test assets, WarFac, as a stand-alone factor model, outperforms various distinguished factor models, explaining 49% of the variance in the test assets. Furthermore, WarFac consistently generates the lowest and statistically insignificant common pricing error (the intercept) for these ML-based nonlinear portfolios compared to other benchmarks. For example, the alphas are 0.4% for WarFac as a solo factor model versus 3%, an average of alphas from the four asset pricing factor model benchmarks that we consider. When we incorporate WarFac into multi-factor benchmarks, the common cross-sectional pricing error dramatically shrinks from 3% to close to zero. 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 asset classes.[1]

Bryzgalova, Pelger, and Zhu (2020) find that ML-based nonlinear portfolios capture complex interactions among many characteristics and nonlinear effects of characteristics on returns. They argue that their test assets are more challenging to price than conventional cross sections. 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

[1] When pricing ML-based nonlinear portfolios, WarFac's return premium slope stands at -36%, compared to -17% for HXZ's long-short portfolios, -8% for HXZ's single-sorted portfolios, and -17% for CZ's single-sorted portfolios.

more overpriced.

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.[2] Hirshleifer, Mai, and Pukthuanthong (2023) further discuss the differences between these measures in aggregate market prediction.

Bybee et al. (2023) 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. 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

[2] In contrast, these two media-based uncertainty measures do not yield significant return premiums as the disaster risk model implies. For details, see Subsection 5.1.

semisupervised topic model to extract war risk from all news in the *NYT* from 1871 to 2019.[3] The key advantage of our semisupervised approach is that *War* is available in real-time, so that our tests are not subject to look-ahead bias.

Notably, ours is the first study to examine whether an empirical measure of rare disaster risks captured by *War* receives a return premium over a broad cross section of assets. Our results confirm this prediction, while recognizing that there is also a possible behavioral interpretation of this relationship.

As discussed earlier, *War* predicts aggregate time series stock and bond returns out of sample. This paper tests whether war risk, as captured by the *War* factor, predicts the cross section of expected returns. 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 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. According to Ang, Chen, and Xing (2006), the downside risk is priced more heavily than the 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)

[3] We use our *War* index from 1926 to 2019 in asset pricing tests (data on portfolio returns becomes available in 1926).

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 but capture few of the very rare but most devastating events. The options data are available for less than 30 years, while our study utilizes 160 years of data since the newspaper's inception. 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.

Our approach offers a distinctive and complementary perspective to these methodologies. WarFac measure provides insights into real-time market perceptions and beliefs concerning future disaster risk, as it is grounded in evidence from media discussion. Asset prices are determined by current market perceptions, which may or may not be unbiased estimates of subsequent realizations. So tests based on proxies for market perceptions get more directly at the immediate determinants of asset prices.

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.[4] In contrast,

[4]When we extend to 49 industry portfolios, WarFac outperforms 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

we consider a much more extensive set of test assets as discussed above and benchmark our pricing results against the 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

This paper uses the sLDA model (Lu et al. 2011) to extract specific news discourse topics. We follow the setup in Hirshleifer, Mai, and Pukthuanthong (2023), 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 (2023); 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,

pricing models which predict negative return premia.

we randomly pick a topic from this document-topic distribution. Finally, at this position, we 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 (2023) 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. Our seed words for *War* include *conflict, tension, terrorism, war*.[5] In addition to *War*, Hirshleifer, Mai, and Pukthuanthong (2023) 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.[6] See Table A.1 for each topic's list of lemmatized seed words.[7]

[5] In the setup of LDA, "tension(s)" tends not to be assigned to *War* in documents that talk little about war (such as articles about tension headaches) and to be assigned to *War* in documents that talk a lot about war (such as articles about international tensions).

[6] 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*.

[7] "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 and bond 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 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.

Although ten years of news articles are used to estimate the model each month, the final topic weights in month t are computed from the news articles of that month only. 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 conduct the standard text processing steps.[8]

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

[8]We follow the text cleaning procedure described in Internet Appendix A of Hirshleifer, Mai, and Pukthuanthong (2023).

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*.

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. A detailed description of the statistics for all extracted topics is provided in Hirshleifer, Mai, and Pukthuanthong (2023).

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 (2023) provide evidence that *War* positively predicts the aggregate stock market return. This section tests whether a factor based on *War* can be used to predict the cross section of expected stock returns. 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 byKozak, 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.[9]

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.[10]

[9] Gourio (2008) use 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.

[10] 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 (2020) 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.

4.2 Asset Pricing Framework

Let the realization at date t of the *War* factor be denoted WarFac_t. To capture factor pricing, we propose the following SDF for excess returns that are affine in WarFac_t:

$$SDF_t = 1 - b \times WarFac_t. \tag{1}$$

The no-arbitrage condition for an asset i's return over the riskfree rate is

$$\begin{aligned} 0 &= \mathbb{E}\left[R^e_{i,t} SDF_t\right] \\ \mathbb{E}\left[R^e_{i,t}\right] &= \underbrace{b \times R^f \operatorname{var}\left(WarFac_t\right)}_{\lambda_{War}} \times \underbrace{\frac{\operatorname{cov}\left(R^e_{i,t}, WarFac_t\right)}{\operatorname{var}\left(WarFac_t\right)}}_{\beta_{i,War}}, \\ \mathbb{E}\left[R^e_{i,t}\right] &= \lambda_{War} \times \beta_{i,War}, \end{aligned} \tag{2}$$

where $R^e_{i,t}$ is the excess return of asset i at time t, $\beta_{i,War}$ denotes the exposure of asset i to the *War* factor, and λ_{War} is the cross-sectional return premium slope associated with the *War* factor. Alternatively, the behavioral interpretation of λ measures the extent to which assets with higher sensitivity to war prospects are overvalued relative to stocks with lower sensitivity.

To estimate $\beta_{i,War}$, and λ_{War}, we conduct the standard two-pass test (Cochrane 2005, Chapter 12). First, for each asset $i = 1, \ldots, N$, we estimate the risk exposures from the time-series regression:

$$R^e_{i,t} = \alpha_i + \beta'_{i,f} F_t + \epsilon_{i,t}, \tag{3}$$

where F_t presents a vector of risk factors. Then, to estimate the cross-sectional return premium slope associated with factors F_t, we perform a cross-sectional regression of time-series average excess returns, $\mathbb{E}\left[R^e_{i,t}\right]$, on risk factor exposures:

$$\mathbb{E}\left[R^e_{i,t}\right] = \mu_{R,i} = \lambda_0 + \beta'_{i,f}\lambda_f + e_i \quad \text{for } i = 1, \ldots, N. \tag{4}$$

We obtain 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.

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 $R^2 (= 1 - \sigma^2_e/\sigma^2_{\mu_R})$ 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. We also report the p-value of the Chi-squared test that all pricing errors are jointly zero (Cochrane 2005, Chapter 12).

Following He, Kelly, and Manela (2017), we construct our *War* factor, denoted as WarFac, as the innovation from an AR(1) model of *War*. We estimate the shock to the *War* in levels, u_t, and convert this to a growth rate by dividing it by the lagged *War*: [11]

$$War_t = \rho_0 + \rho \times War_{t-1} + u_t \quad \text{and} \tag{5}$$

$$WarFac_t = \frac{u_t}{War_{t-1}}. \tag{6}$$

[11] We use data on our *War* index from January 1926 to October 2019 to estimate the coefficients of the AR(1) process because data on portfolio returns first became available in 1926. Our results are not sensitive to the different choices of this sample. Using the whole sample from 1871 to 2019 or using log difference to construct the WarFac yield similar results.

4.3 Test Assets

We consider a large set of test assets constructed from a wide range of characteristics, including:[12,13]

[1] 138 long-short anomaly portfolios from Hou, Xue, and Zhang (2020) (HXZ),

[2] 1372 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 (2020),

[5] Our own constructed 128 long-short anomaly portfolios based on HXZ,

[6] Our own constructed 2190 non-linear portfolios.[14]

To explore whether WarFac is an economy-wide factor that helps explain various anomaly portfolios, we include a variety of testing assets, both traditional and complex.[15] 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 1372 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 (2020). 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

[12] 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.

[13] 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.

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

[15] See Internet Appendix D for the detailed construction and the coverage of our testing assets.

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 testing asset set for a robustness check. Finally, we build nonlinear portfolios based on three polynomials. See Internet Appendix D.2 for a description of how these anomaly portfolios are constructed.

4.4 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). It is infeasible to compare all existing factor models; therefore, we concentrate on 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 conduct the two-pass test presented in equations (3) and (4) to estimate factor return premia and to assess model fit.

The first set of test assets that we consider are the 138 long-short anomaly portfolios from HXZ in Panel A of Table 1. 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 ($t = -2.74$). Its monthly return premium is -17.25%. 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 has a monthly standard deviation of 14% over 1972-2016, so its first-stage betas are much smaller than those produced by traded factors. As a result, the return premium per loading unit (its price of risk under rational factor pricing) is much larger than that of the other traded factors.

WarFac maintains its significance even after introducing other factors to the model. Lewellen (2022) argues 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. In the last specification, when we include all factors from standard factor models, WarFac yields a return premium of -8.9%, significant at the 1% level. The introduction of WarFac to the FF6 factor model leads to an increase in the model explanatory power (R^2) by 9%. Adding WarFac to M4, DHS, and Q5 results in a respective increase in the explanatory power of 6%, 16%, and 2%. When considered as a solo factor, WarFac has an R^2 of 44% and an MAPE of 0.27%, while FF6, M4, DHS, and Q5 have R^2's 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. However, we reject the null that pricing errors are jointly zero under all models.

We next evaluate the performance of WarFac in pricing the 1372 single-sorted portfolios from HXZ as test assets in Panel B of Table 1. The monthly return premium for WarFac is reduced by more than half, from -17% to -8%, and the absolute t-statistic diminishes from 2.67 to 2.36. 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 4% in their explanatory power. However, as a single-factor model, WarFac does not fit these portfolios well, as its R^2 is only 18% 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 4.7%, significant at the 1% level, when tested against all factors. For this set of test assets, MAPEs of all models are around 0.1%, and under all models except FF6, we fail to reject the null that pricing errors are jointly zero.

Panel C reports the results for the 904 single-sorted portfolios of Chen and Zimmermann (2022). This set of test assets is gaining popularity in the literature 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 -17.2%, significant at the 1% level, and explains 27% 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 M4 increases the R^2 from 12% to 34%.

When the test assets are the 360 ML-based nonlinear portfolios, WarFac yields a return premium of -36% per month and an insignificant common pricing error (intercept), as seen in the first column in Panel D of Table 1. Remarkably, the monthly return premium for loadings on WarFac increases (in absolute magnitude) to -57%, -47%, -49%, and -48% after including FF6, M4, DHS, and Q5. Furthermore, including WarFac enhances the explanatory power (R^2) of the FF6, M4, DHS, and Q5 models by 27%, 21%, 28%, and 11%, respectively, and reduces the MAPEs of these models by 0.07% on average. For this set of test assets, the explanatory power of the WarFac as a single-factor model is 49%, which is higher than FF6 (41%), M4 (40%), DHS (35%), and lower than Q5 (58%). Moreover, the addition of *War* 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 on average.

When all factors are included, WarFac has a return premium of 21%, significant at the 1% level. Also, by adding WarFac to FF6, DHS, and Q5, we fail to reject the null that the pricing errors are jointly zero.

These findings indicate that WarFac effectively prices various assets—especially 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 2190 nonlinear portfolios are constructed from the characteristics of up to three polynomials (see Internet Appendix D). 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 20% when pricing 360 ML-based nonlinear portfolios 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 Pricing Results: 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 our 2 *War* related factors and 13 traded factors from benchmark factor models.

The WarFac mimicking portfolio is constructed as the fitted value from a projection of WarFac onto basis assets (see Section 6 for details). Table 2 shows that WarFac, the WarFac mimicking portfolio, 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. In 4 out of 6 sets of test assets (except single-sorted portfolios from HXZ and our own constructed nonlinear portfolios), R^2 produced by WarFac is higher than that of all traded factors. For the ML-based portfolios from Bryzgalova, Pelger, and Zhu (2020), WarFac's R^2 (49%) is nearly 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 2 indicate that it is not easy for any traded factor to perform well in pricing our collection of test portfolios. This further strengthens our conclusion that WarFac is a strong risk factor.

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* innovations negatively predict 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).[16] This section investigates whether WarFac contains information beyond these two measures by performing horse-race cross-sectional return prediction tests.

We conduct the cross-sectional tests with the factors constructed from *War*, NVIX^2, and geopolitical risks (GPR).[17] We construct these factors using equation (6). As reported in Table 3, across all three sets of test assets, the economic and statistical magnitudes of WarFac remain almost unchanged in the presence of NVIX^2 and GPR factors, implying *War* presents distinct information. Meanwhile, NVIX^2 and GPR command positive risk premia when used alone though their economic and statistical significance varies across test assets. When tested against WarFac, the NVIX^2 and GPR factors are completely subsumed across three groups of 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.

[16] We thank the authors of these papers for making their data available.
[17] We use NVIX^2 to be consistent with the original paper.

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

We next investigate whether the news-based WarFac prices industry portfolios. Berkman, Jacobsen, and Lee (2011) measure empirical disaster risks by counting the number of crisis events each month.[18] 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 counts price the Fama-French 30 industry portfolios with negative return premiums. We test here whether WarFac has incremental predictive power beyond real-world crisis factors.

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:

$$R^e_{i\tau} = \alpha_{it} + \beta_{it} X_\tau + \beta^{MKT}_{it} MKT_\tau + \beta^{SMB}_{it} SMB_\tau + \beta^{HML}_{it} HML_\tau + \epsilon_{i\tau}, \qquad (7)$$

where $R^e_{i\tau}$ is the excess return of portfolio i over month $t-59$ to month t, and X is either the *War* factor (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

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

previous month's betas computed in the previous step:

$$R^e_{it} = \lambda_{0t} + \lambda_t\beta_{i,t-1} + \lambda_t^{MKT}\beta_{i,t-1}^{MKT} + \lambda_t^{SMB}\beta_{i,t-1}^{SMB} + \lambda_t^{HML}\beta_{i,t-1}^{HML} + e_{it}, \tag{8}$$

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 4, the test assets are 30 industry portfolios. 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 0.3%, significant at the 5% level. In contrast, the return premium of CWarFac is only -0.21%, 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 CrisisFac each yield similar return premiums of -0.25%, significant at the 5% level. In contrast, the return premium of CWarFac is not significant. In the last column, Warfac dominates the other two event-based crisis factors when all three crisis factors are included.

Overall, we find a factor based upon our 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 previous analysis constructs WarFac as a shock from the first-order autoregressive process. This is a computationally simple approach, but the resulting factor is non-traded. Non-traded factors may contain noise unrelated to returns, which 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). As discussed in Subsection 4.4, the estimated return premium for WarFac loadings is economically substantial at around -22% per month across test assets. Still, this estimate may be inflated due to noise.

In this section, we form a traded version of the WarFac or the WarFac mimicking portfolio by projecting WarFac onto the space of excess returns. WarFac mimicking portfolio is in the form of a traded return. Compared to the shock, the mimicking portfolio captures the exposure of assets to War risk and provides insights into the potential alpha and Sharpe ratio generated by the WarFac loadings. The drawback is that constructing this portfolio requires more data and computational resources and may be subject to misspecification or estimation errors. We present the WarFac mimicking portfolio results to ensure robust conclusions and address the issue of inflated estimates of the return premium slope discussed above.

6.1 Construction of WarFac Mimicking Portfolio

Adrian, Etula, and Muir (2014) suggest that most non-traded factors are combinations of a factor mimicking portfolio (FMP) and noise, and exhibit inflated return premium slope ("market price of risk") owing to noise and measurement errors that are uncorrelated with returns. To tackle the inflation estimation issue of non-traded factors, they advocate constructing FMPs and re-performing tests. 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 WarFac mimicking portfolio, following the time-series approach of Adrian, Etula, and Muir (2014), we project our nontraded WarFac onto the space of excess returns:

$$WarFac_t = \alpha + \beta' R^e + \epsilon_t, \tag{9}$$

where R^e is the vector of excess returns on 30 portfolios consisting of 10 equal-weighted portfolios sorted on the market value of equity, 10 equal-weighted portfolios sorted on book-market ratio, and 10 value-weighted portfolios sorted on past 12-month returns (i.e., momentum) downloaded from Ken French's website.[19] 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 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 *WarFac Mimicking Portfolio* (WMP) as the fitted value.

$$WMP_t = \hat{\beta}' R^e_t, \tag{10}$$

where $\hat{\beta}$ is estimated via OLS from 1926 to 2019.[20]

Panel A of Table 5 reports the summary statistics of WMP and other traded factors

[19] 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.

[20] Even though WarFac is missing in September and October 1978 due to strikes at the *NYT*, we calculate WMP without a gap from 1926 to 2019. After estimating the projection coefficient $\hat{\beta}$ using WarFac, we apply $\hat{\beta}$ to non-missing portfolio data.

over 1972-2016. WMP has a monthly average return of -0.87%, consistent with the negative return premium estimate for WarFac, and a monthly standard deviation of return of 3.26%, yielding an absolute annualized Sharpe ratio of 0.92. The absolute Sharpe ratio of WMP is lower than that of PEAD (1.16) and R_EG (1.53) and higher than those of the remaining factors.

6.2 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:

$$WMP_t = \alpha + \beta^{'} F_t + \epsilon_t, \tag{11}$$

where F_t is the vector of traded factors. As reported in Panel B of Table 5, WMP has a monthly alpha of around 0.6%, 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 that mean-variance dominates the benchmark factors (Back 2018, page 143). Furthermore, all factors combined explain only 22% of the time-series variation of WMP.

6.3 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 in the previous sections. 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 6. The results for our

128 own-constructed anomaly portfolios and our 2,190 own-constructed nonlinear portfolios are reported in Table B.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. The monthly return premium for loadings on WMP is -1% for the 138 anomaly characteristic portfolios from HXZ, -0.86% for the 1372 single-sorted portfolios from HXZ, -1.35% for the 904 single-sorted portfolios from CZ, -2.51% for the 360 ML-based nonlinear portfolios, -1.19% for our own-constructed 128 anomaly characteristic portfolios, and -1.35% for our 2019 own-constructed nonlinear portfolios. Hence, the absolute return premium for loadings on war risk is, on average, 1.4% per month (or 16.6% per annum) across test assets. Except for when WMP is tested against M4 and Q5 on the 138 anomaly characteristic portfolios from HXZ and against all factors on the 360 ML-based portfolios, the risk premia of WMP remains significant at least the 5% level in all other specifications across all sets of test assets. As a solo-factor model, the average R^2 for WMP across six sets of test assets is 28%. Our result remains robust using our own constructed long-short and nonlinear portfolios.

These results indicate that the pricing power of WMP constructed from 30 portfolios aligns closely with that of the WarFac generated from a shock in the first-order autoregressive process.

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 premium: the protocol of factor identification proposed by Pukthuanthong, Roll, and

Subrahmanyam (2019) and the three-pass test by 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). They assert that a priced risk factor must be related to the covariance matrix of returns, be priced in the cross section of returns, and yield a reward-to-risk ratio reasonable enough to be consistent with risk pricing. We present a detailed exposition of these criteria in Internet Appendix C.[21]

The protocol of factor identification applies only to tradable factors. Hence, to use the protocol, a nontraded factor such as the shock to *War* index must be converted into a tradable version by constructing a mimicking portfolio. Essentially, the first condition of Pukthuanthong, Roll, and Subrahmanyam (2019) examines whether a factor is in the SDF, i.e., is associated with aggregate risk. The second condition ensures a factor is priced and commands a return premium. When factors are unrelated to the covariance matrix or not in the SDF but still demand significant risk premia, it implies that these factors capture some risks that are not directly related to the underlying economic state variables or investors' preferences. As reported in Table C.1 and Table C.2, WMP passes these conditions, consistent with it being a priced risk factor.

[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).

7.2 Three-Pass test

Our second robustness check applies the three-pass test proposed by Giglio and Xiu (2021), designed for estimating an observable factor's risk premium when not all factors in the model are specified or observed.

The test has three steps. First, a principal component analysis is conducted 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 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 7. WMP, MOM, and FIN are the only factors having a significant estimated risk premia across all six test asset sets. However, the estimated risk premium of FIN is only significant at 10% in two sets of test assets. Even though other traded factors do not consistently yield significant estimated risk 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 7).

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.

8 Conclusion

This paper constructs a war factor based on the measure of *War* media textual discourse proposed by Hirshleifer, Mai, and Pukthuanthong (2023) to evaluate shared 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 demands a significant negative risk 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.

Overall, 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 asset 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.

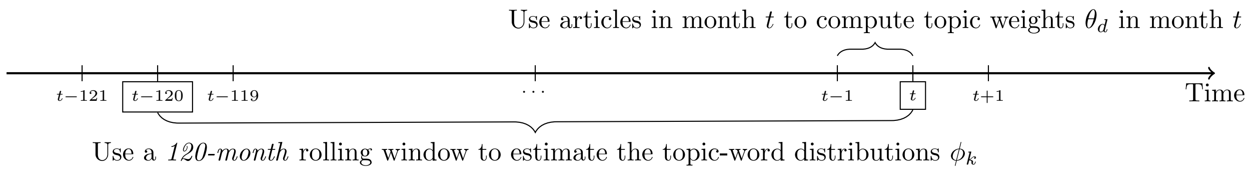


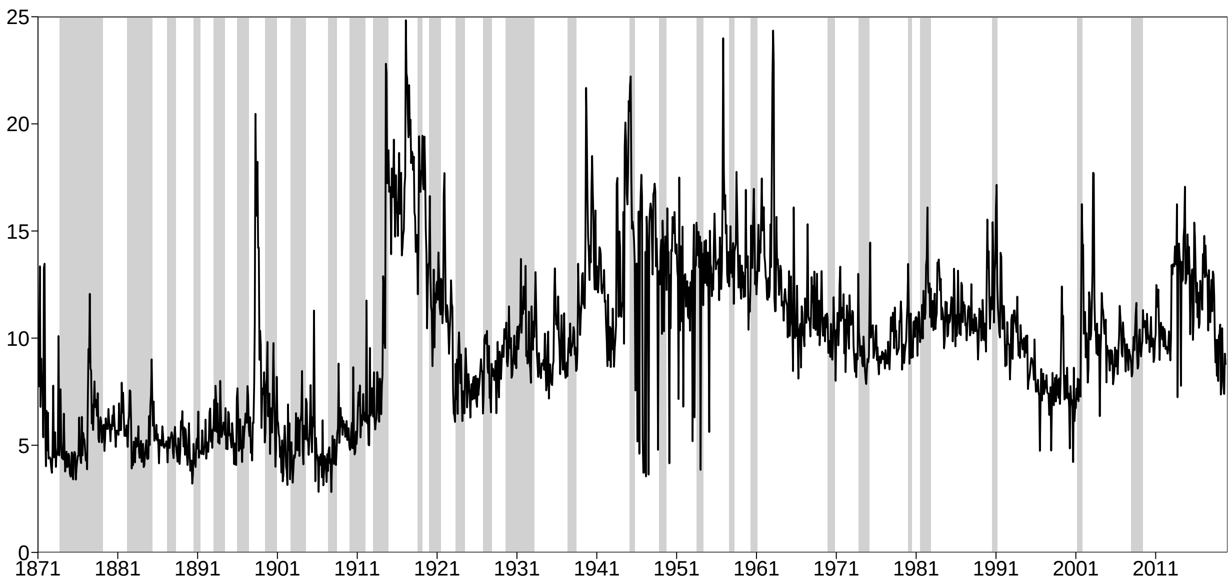
Figure 2. Narrative Contents

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

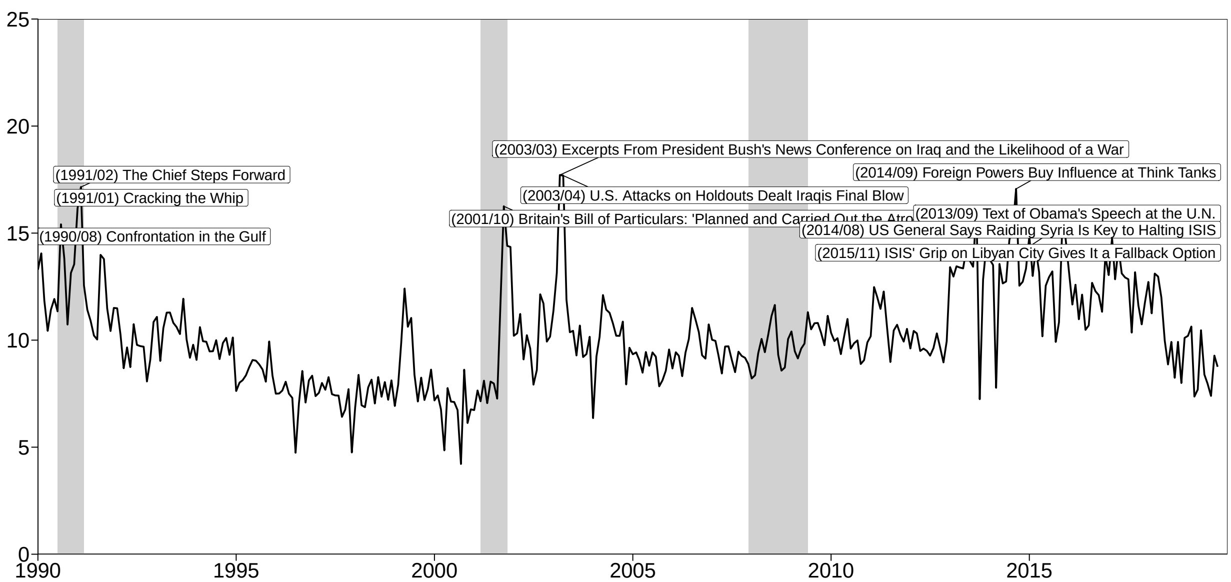


Table 1
War Factor and Risk Premium

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

$$\bar{R}^e_{i,t} = \lambda_0 + \beta'_{i,f}\lambda_f + e_i,$$

where $\bar{R}^e_{i,t}$ is the time-series average return of portfolio i, $\beta_{i,f}$ 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 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 (2020) in Panel D. "WarFac" is the scaled innovations in *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 risk premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percentages, MAPE is mean absolute pricing error in percentages, and $p(\text{PE} = 0)$ is the p-value of the Chi-squared test that pricing errors are jointly zero. 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)
Intercept	0.24 ***	0.16 ***	0.15 ***	0.09 ***	0.10 ***	0.15 ***	0.14 ***	0.11 ***	0.10 ***	0.07 ***
	(3.93)	(7.08)	(4.81)	(3.23)	(3.00)	(4.67)	(3.60)	(2.78)	(2.74)	(3.01)
WarFac	-17.25 ***					-16.00 ***	-13.60 ***	-18.27 ***	-8.14 **	-8.89 ***
	(-2.74)					(-4.81)	(-4.56)	(-3.32)	(-2.53)	(-3.27)
MKT		0.48	0.89 **	1.14 ***		0.41	0.69 *	1.05 **		0.65 *
		(1.50)	(2.51)	(2.98)		(1.01)	(1.65)	(2.01)		(1.88)
SMB		0.05	-0.02			-0.00	-0.05			0.18
		(0.30)	(-0.15)			(-0.02)	(-0.26)			(0.98)
HML		0.27				0.29				0.55 ***
		(1.60)				(1.41)				(3.04)
RMW		0.28 **				0.23				0.19
		(2.27)				(1.62)				(1.42)
CMA		0.54 ***				0.51 ***				0.18
		(4.91)				(3.95)				(1.50)
MOM		0.61 ***				0.77 ***				0.52 **
		(2.91)				(3.40)				(2.36)
MGMT			0.71 ***				0.57 ***			0.66 ***
			(4.50)				(3.17)			(3.54)
PERF			0.47 *				0.58 **			-0.07
			(1.93)				(2.07)			(-0.26)
PEAD				0.36 **				0.55 **		0.45 ***
				(2.19)				(2.49)		(2.96)
FIN				0.96 ***				0.79 ***		0.89 ***
				(4.64)				(3.32)		(3.78)
R_MKT					0.66 *				0.58	
					(1.87)				(1.59)	
R_ME					0.25				0.29 *	0.28 *
					(1.48)				(1.65)	(1.70)
R_IA					0.44 ***				0.39 ***	0.36 ***
					(3.66)				(3.20)	(2.77)
R_ROE					0.33 **				0.35 **	0.43 ***
					(2.40)				(2.49)	(3.15)
R_EG					0.80 ***				0.70 ***	0.75 ***
					(6.05)				(4.63)	(6.11)
R^2	44	59	65	51	77	68	71	67	79	83
MAPE	0.27	0.21	0.20	0.24	0.15	0.18	0.18	0.19	0.15	0.13
$p(PE = 0)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
N	138	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532	532

Table 1
War Factor and Risk Premium (Cont.)

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.72 ***	0.43 **	0.25	-0.22	0.35	0.42 *	0.23	-0.28	0.33	0.23
	(3.45)	(2.12)	(1.11)	(-0.81)	(1.55)	(1.92)	(0.94)	(-0.92)	(1.39)	(1.01)
WarFac	-8.42 **					-5.80 ***	-5.83 ***	-7.47 ***	-4.64 ***	-4.69 ***
	(-2.36)					(-4.77)	(-4.62)	(-4.07)	(-3.76)	(-3.82)
MKT		0.16	0.34	0.84 **		0.17	0.36	0.91 **		0.39
		(0.55)	(1.08)	(2.47)		(0.56)	(1.11)	(2.44)		(1.27)
SMB		0.16	0.20			0.12	0.15			0.20
		(1.08)	(1.31)			(0.85)	(0.98)			(1.35)
HML		0.30 **				0.31 **				0.50 ***
		(1.98)				(1.98)				(3.23)
RMW		0.18				0.20 *				0.16
		(1.56)				(1.65)				(1.36)
CMA		0.20 **				0.22 **				0.18 *
		(2.06)				(2.25)				(1.80)
MOM		0.58 ***				0.63 ***				0.45 **
		(2.84)				(3.07)				(2.22)
MGMT			0.46 ***				0.44 ***			0.38 **
			(2.89)				(2.69)			(2.55)
PERF			0.47 **				0.51 **			0.29
			(2.12)				(2.25)			(1.35)
PEAD				0.32 **				0.40 **		0.37 ***
				(2.13)				(2.50)		(3.19)
FIN				0.57 ***				0.59 ***		0.57 ***
				(2.84)				(2.83)		(2.86)
R_MKT					0.24				0.27	
					(0.77)				(0.84)	
R_ME					0.34 **				0.34 **	0.26 *
					(2.29)				(2.27)	(1.83)
R_IA					0.27 **				0.27 **	0.26 ***
					(2.43)				(2.33)	(2.62)
R_ROE					0.23 *				0.25 *	0.38 ***
					(1.76)				(1.94)	(3.04)
R_EG					0.61 ***				0.58 ***	0.61 ***
					(5.65)				(5.25)	(6.20)
R^2	18	42	43	34	55	46	47	42	57	65
MAPE	0.11	0.09	0.09	0.09	0.08	0.08	0.08	0.09	0.08	0.07
$p(PE = 0)$	1.00	0.01	0.17	0.56	0.96	0.96	1.00	1.00	1.00	1.00
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532	532

Table 1
War Factor and Risk Premium (Cont.)

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.95 **	0.93 ***	0.76 ***	1.59 ***	0.65 ***	0.67 ***	0.45 **	0.74 ***	0.46 **	0.30
	(2.55)	(5.93)	(4.76)	(7.04)	(3.28)	(3.62)	(2.26)	(2.62)	(2.33)	(1.28)
WarFac	-17.20 ***					-13.67 ***	-14.60 ***	-21.56 ***	-10.54 ***	-9.91 ***
	(-3.01)					(-4.44)	(-3.99)	(-4.02)	(-3.51)	(-3.53)
MKT		-0.40	-0.24	-0.77 ***		-0.11	0.13	0.09		0.30
		(-1.56)	(-0.91)	(-2.69)		(-0.38)	(0.45)	(0.28)		(0.98)
SMB		0.35 **	0.47 ***			0.18	0.21			0.13
		(2.32)	(3.00)			(1.19)	(1.39)			(0.79)
HML		0.30 **				0.31 **				0.57 ***
		(2.05)				(1.96)				(3.34)
RMW		-0.02				0.20				-0.02
		(-0.11)				(1.42)				(-0.13)
CMA		0.84 ***				0.73 ***				0.41 ***
		(7.00)				(5.60)				(2.93)
MOM		0.56 **				0.82 ***				0.77 ***
		(2.48)				(3.57)				(3.26)
MGMT			0.66 ***				0.71 ***			0.65 ***
			(3.84)				(3.46)			(3.51)
PERF			0.58 **				0.83 ***			1.04 ***
			(2.39)				(2.91)			(4.40)
PEAD				-0.04				0.50 *		0.38 *
				(-0.20)				(1.72)		(1.76)
FIN				0.24				0.71 ***		1.42 ***
				(1.10)				(2.74)		(5.19)
R_MKT					-0.03				0.16	
					(-0.11)				(0.58)	
R_ME					0.40 ***				0.38 **	0.35 **
					(2.60)				(2.46)	(2.32)
R_IA					0.42 ***				0.41 **	0.65 ***
					(2.58)				(2.39)	(4.17)
R_ROE					0.20				0.39 **	0.86 ***
					(1.04)				(2.18)	(4.68)
R_EG					1.48 ***				1.35 ***	1.70 ***
					(8.02)				(6.83)	(10.34)
R^2	27	41	43	12	57	47	51	34	60	66
MAPE	0.17	0.14	0.14	0.19	0.12	0.14	0.13	0.16	0.12	0.11
$p(PE=0)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	904	904	904	904	904	904	904	904	904	904
T	532	532	532	532	532	532	532	532	532	532

Table 1
War Factor and Risk Premium (Cont.)

Panel D: ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.43	3.39 ***	3.28 ***	4.22 ***	2.11 ***	-0.27	0.35	-0.43	-0.01	-0.34
	(0.52)	(6.80)	(7.51)	(6.07)	(2.73)	(-0.24)	(0.38)	(-0.40)	(-0.01)	(-0.39)
WarFac	-36.37 ***					-56.76 ***	-47.49 ***	-48.64 ***	-47.64 ***	-21.34 ***
	(-2.79)					(-3.38)	(-3.51)	(-3.42)	(-3.39)	(-2.85)
MKT		-3.39 ***	-3.24 ***	-3.86 ***		0.64	0.05	0.79		0.56
		(-6.06)	(-6.40)	(-5.47)		(0.55)	(0.05)	(0.74)		(0.60)
SMB		0.18	0.12			-0.71 **	-0.90 ***			-0.05
		(1.04)	(0.64)			(-2.35)	(-3.12)			(-0.24)
HML		1.31 ***				0.81 *				0.66 *
		(6.24)				(1.77)				(1.71)
RMW		0.20				1.28 **				0.44
		(0.95)				(2.54)				(1.15)
CMA		0.28 *				0.04				0.36
		(1.81)				(0.10)				(1.09)
MOM		0.21				1.45 ***				1.12 ***
		(0.86)				(3.42)				(3.37)
MGMT			1.32 ***				1.00 **			-0.35
			(7.13)				(2.40)			(-0.83)
PERF			0.03				0.95			1.68 **
			(0.11)				(1.55)			(2.47)
PEAD				-0.56 **				0.66		0.60
				(-2.09)				(1.17)		(0.99)
FIN				0.83 **				2.08 ***		2.51 ***
				(2.54)				(3.46)		(3.23)
R_MKT					-1.76 **				0.50	
					(-2.17)				(0.49)	
R_ME					-0.15				-0.16	0.22
					(-0.66)				(-0.51)	(0.86)
R_IA					0.24				0.27	0.11
					(0.93)				(0.76)	(0.30)
R_ROE					-0.17				1.02 **	2.18 ***
					(-0.41)				(2.32)	(3.72)
R_EG					3.39 ***				1.71 **	3.69 ***
					(5.95)				(2.16)	(6.24)
R^2	49	41	40	35	58	68	61	63	69	87
MAPE	0.50	0.49	0.49	0.53	0.45	0.39	0.44	0.43	0.40	0.23
$p(PE = 0)$	0.00	0.00	0.00	0.00	0.00	1.00	0.04	0.21	0.41	0.29
N	360	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532	532

Table 2
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:

$$\bar{R}^e_{i,t} = \lambda_0 + \beta_{i,f}\lambda + e_i,$$

where $\bar{R}^e_{i,t}$ is the time-series average return of portfolio i, $\beta_{i,f}$ is the factor exposure of portfolio i estimated via a time-series regression of portfolio return onto factor, and λ_f is the factor risk 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 (2020) in Panel D, own constructed anomalies in Panel E, and own constructed nonlinear portfolios in Panel F. "WarFac" is the scaled 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 risk premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percentages, MAPE is mean absolute pricing error in percentages, and $p(\text{PE} = 0)$ is the p-value of the Chi-squared test that pricing errors are jointly zero. 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
λ_0	0.24 ***	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 ***
	(3.93)	(5.82)	(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)
λ	-17.25 ***	-1.00 ***	-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 ***
	(-2.74)	(-2.99)	(-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	44	29	24	4	21	9	13	35	37	7	4	34	39	8	30
MAPE	0.27	0.32	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
$p(PE = 0)$	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	0.00
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
λ_0	0.72 ***	0.69 ***	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 ***
	(3.45)	(3.52)	(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)
λ	-8.42 **	-0.86 ***	-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 *
	(-2.36)	(-2.61)	(-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	18	23	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
$p(PE = 0)$	1.00	0.01	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
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 2
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
λ_0	0.95 **	0.71 ***	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 ***
	(2.55)	(2.76)	(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)
λ	-17.20 ***	-1.35 ***	-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
	(-3.01)	(-4.13)	(-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	27	33	12	-0	15	1	2	23	13	1	-0	9	18	0	7
MAPE	0.17	0.16	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
$p(PE=0)$	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	0.00
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 (2020)

	WarFac	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ_0	0.43	0.01	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 ***
	(0.52)	(0.02)	(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)
λ	-36.37 ***	-2.51 ***	-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 ***
	(-2.79)	(-4.85)	(-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	49	31	24	0	22	2	3	28	15	3	0	13	21	1	9
MAPE	0.50	0.61	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
$p(PE=0)$	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	0.00
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
λ_0	0.09 *	0.08 ***	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
	(1.77)	(2.81)	(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)
λ	-19.99 ***	-1.19 ***	-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
	(-2.89)	(-3.90)	(-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	31	23	3	-1	7	6	0	11	7	2	5	4	10	0	4
MAPE	0.31	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
$p(PE=0)$	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	0.00
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
λ_0	0.99 ***	0.79 ***	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 ***
	(3.14)	(2.87)	(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)
λ	-11.13 ***	-1.35 ***	-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 *
	(-3.55)	(-4.34)	(-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	25	27	13	29	19	20	36	30	25	7	27	33	18	28
MAPE	0.10	0.09	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
$p(PE=0)$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
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 3
Cross-Sectional Tests: *War* versus NVIX^2 and GPR

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

$$\bar{R}^e_{i,t} = \lambda_0 + \beta'_{i,f}\lambda_f + e_i,$$

where $\bar{R}^e_{i,t}$ is the time-series average return of portfolio i, $\beta_{i,f}$ 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 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 (2020) in Panel D. *WarFac* is the scaled innovations in *War*. *NVIX2Fac* is the scaled innovations in NVIX^2 from Manela and Moreira (2017), and *GPRFac* is the scaled innovations in geopolitical risk (GPR) from Caldara and Iacoviello (2022). Reported are monthly risk premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percentages, MAPE is mean absolute pricing error in percentages, and $p(\text{PE} = 0)$ is p-value of the Chi-squared test that pricing errors are jointly zero. 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	0.25 ***	0.22 ***	0.18 ***	0.16 ***
	(4.26)	(5.70)	(5.46)	(3.25)
WarFac	-16.52 ***			-14.90 **
	(-2.71)			(-2.05)
NVIX2Fac		11.13 **		-2.05
		(2.44)		(-0.28)
GPRFac			18.16 **	10.86
			(2.00)	(0.93)
R^2	40	19	9	60
MAPE	0.29	0.34	0.36	0.22
$p(PE = 0)$	0.00	0.00	0.00	0.00
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	0.71 ***	0.92 ***	0.70 ***	0.84 ***
	(3.37)	(4.66)	(3.68)	(3.68)
WarFac	-8.34 **			-7.68 ***
	(-2.33)			(-2.72)
NVIX2Fac		5.35		0.18
		(1.29)		(0.04)
GPRFac			6.85	1.73
			(1.58)	(0.42)
R^2	17	8	3	24
MAPE	0.11	0.12	0.12	0.11
$p(PE = 0)$	1.00	0.00	0.00	1.00
N	1372	1372	1372	1372
T	522	522	522	522

Table 3
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	0.89 **	1.38 ***	1.02 ***	1.14 ***
	(2.48)	(6.09)	(5.14)	(3.39)
WarFac	-16.14 ***			-12.96 **
	(-2.98)			(-2.03)
NVIX2Fac		8.96 *		0.49
		(1.83)		(0.07)
GPRFac			17.04	4.23
			(1.36)	(0.49)
R^2	25	12	6	32
MAPE	0.17	0.19	0.19	0.16
$p(PE = 0)$	0.00	0.00	0.00	0.00
N	904	904	904	904
T	522	522	522	522

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	(1)	(2)	(3)	(4)
Intercept	0.35	2.71 ***	0.92 ***	1.93 ***
	(0.44)	(8.28)	(3.42)	(2.78)
WarFac	-36.13 ***			-29.73 **
	(-2.76)			(-2.04)
NVIX2Fac		32.13 ***		19.95
		(4.15)		(1.20)
GPRFac			32.15	-19.90
			(1.47)	(-0.77)
R^2	45	29	4	57
MAPE	0.54	0.59	0.69	0.45
$p(PE = 0)$	0.00	0.00	0.00	0.00
N	360	360	360	360
T	522	522	522	522

Table 4
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 risk premiums in month t. Reported are the time series averages of risk premiums 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 risk premiums 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	0.85 ***	0.85 ***	0.74 ***	0.81 ***
	(4.77)	(4.95)	(4.20)	(4.46)
WarFac	-0.24 **			-0.30 **
	(-2.00)			(-2.32)
CrisisFac		-0.37 ***		-0.30 **
		(-3.20)		(-2.30)
CWarFac			-0.26 **	-0.21 *
			(-2.31)	(-1.79)
MKT	-0.12	-0.11	0.13	0.06
	(-0.63)	(-0.58)	(0.59)	(0.27)
SMB	0.14	0.09	0.08	0.13
	(1.29)	(0.83)	(0.72)	(1.12)
HML	0.16	0.17	0.14	0.16
	(1.35)	(1.38)	(1.11)	(1.26)
R^2	21	20	19	22

Table 4
Cross-Sectional Tests: *War* versus Crisis Events (Cont.)

Panel B: 49 Industry Portfolios

	(1)	(2)	(3)	(4)
Intercept	0.68 ***	0.71 ***	0.73 ***	0.68 ***
	(4.20)	(4.44)	(4.63)	(4.40)
WarFac	-0.25 **			-0.35 ***
	(-2.19)			(-2.94)
CrisisFac		-0.24 **		-0.20 *
		(-2.48)		(-1.75)
CWarFac			-0.09	-0.15
			(-0.80)	(-1.27)
MKT	0.06	0.04	0.14	0.17
	(0.32)	(0.22)	(0.73)	(0.91)
SMB	0.11	0.09	0.10	0.12
	(1.17)	(0.97)	(0.92)	(1.13)
HML	0.23 **	0.21 **	0.22 **	0.26 **
	(2.11)	(1.97)	(2.02)	(2.26)
R^2	17	17	16	19

Table 5
War Mimicking Portfolio: Summary Statistic and Spanning Test

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 regression of WMP onto factors.

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

where F_t is the vector of traded factors. Alpha and R^2 are in percentages, 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	-0.87	0.54	0.16	0.40	0.28	0.35	0.65	0.66	0.63	0.62	0.79	0.27	0.41	0.54	0.83
SD	3.26	4.55	3.10	2.93	2.34	1.95	4.43	2.81	3.92	1.88	3.89	3.10	1.85	2.58	1.87
SR	-0.92	0.41	0.17	0.48	0.41	0.63	0.51	0.81	0.55	1.14	0.71	0.31	0.76	0.72	1.53

Table 5

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

Panel B: Spanning Test

	(1)	(2)	(3)	(4)	(5)
Alpha (%)	-0.52 ***	-0.55 ***	-0.66 ***	-0.58 ***	-0.59 ***
	(-3.51)	(-3.35)	(-3.72)	(-3.82)	(-3.95)
MKT	-0.05	-0.04	-0.03		-0.04
	(-1.16)	(-0.87)	(-0.71)		(-1.00)
SMB	-0.10	-0.15 **			0.18
	(-1.44)	(-2.21)			(0.73)
HML	-0.32 ***				-0.43 ***
	(-3.69)				(-4.05)
RMW	0.02				-0.01
	(0.28)				(-0.11)
CMA	-0.37 ***				-0.51 **
	(-3.17)				(-2.45)
MOM	-0.08				-0.04
	(-1.53)				(-0.73)
MGMT		-0.39 ***			0.33 **
		(-3.38)			(2.51)
PERF		-0.02			-0.19 **
		(-0.33)			(-2.36)
PEAD			-0.05		-0.05
			(-0.40)		(-0.48)
FIN			-0.20 **		-0.05
			(-2.47)		(-0.53)
R_MKT				-0.01	
				(-0.13)	
R_ME				-0.13 **	-0.20
				(-2.16)	(-0.85)
R_IA				-0.58 ***	0.02
				(-4.49)	(0.12)
R_ROE				0.14 *	0.28 **
				(1.70)	(2.45)
R_EG				-0.10	-0.05
				(-1.01)	(-0.47)
R^2(%)	18	7	4	13	22

Table 6
War Mimicking Portfolio and Risk Premium

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

$$\bar{R}^e_{i,t} = \lambda_0 + \beta'_{i,f}\lambda_f + e_i,$$

where $\bar{R}^e_{i,t}$ is the time-series average return of portfolio i, $\beta_{i,f}$ 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 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 (2020) 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 risk premium λ and t-statistic with Shanken (1992) correction. R^2 is cross-sectional R^2 in percentages, MAPE is mean absolute pricing error in percentages, and $p(\text{PE} = 0)$ is p-value of the Chi-squared test that pricing errors are jointly zero. 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)
Intercept	0.23 ***	0.16 ***	0.14 ***	0.09 ***	0.10 ***	0.16 ***	0.14 ***	0.10 ***	0.09 ***	0.07 ***
	(5.67)	(7.08)	(4.74)	(3.12)	(2.99)	(6.72)	(5.27)	(3.52)	(3.28)	(3.03)
WMP	-0.99 ***					-1.28 ***	-0.48	-0.88 **	-0.52	-1.06 ***
	(-2.99)					(-3.20)	(-1.08)	(-2.32)	(-1.15)	(-2.68)
MKT		0.42	0.85 **	1.04 ***		0.51	0.87 **	0.76 **		0.72 **
		(1.32)	(2.44)	(2.70)		(1.56)	(2.53)	(2.23)		(2.13)
SMB		0.03	-0.05			-0.09	-0.08			0.08
		(0.21)	(-0.29)			(-0.53)	(-0.43)			(0.45)
HML		0.26				0.20				0.52 ***
		(1.57)				(1.16)				(3.03)
RMW		0.28 **				0.23 *				0.20
		(2.27)				(1.83)				(1.58)
CMA		0.54 ***				0.57 ***				0.18
		(4.93)				(5.09)				(1.59)
MOM		0.57 ***				0.58 ***				0.38 *
		(2.75)				(2.79)				(1.79)
MGMT			0.70 ***				0.67 ***			0.71 ***
			(4.48)				(4.27)			(3.95)
PERF			0.44 *				0.46 *			-0.12
			(1.82)				(1.90)			(-0.43)
PEAD				0.33 **				0.42 ***		0.48 ***
				(2.06)				(2.74)		(3.38)
FIN				0.97 ***				0.81 ***		0.77 ***
				(4.65)				(4.02)		(3.42)
R_MKT					0.62 *				0.66 *	
					(1.78)				(1.83)	
R_ME					0.22				0.19	0.11
					(1.26)				(0.97)	(0.63)
R_IA					0.44 ***				0.42 ***	0.41 ***
					(3.69)				(3.93)	(3.42)
R_ROE					0.31 **				0.31 **	0.40 ***
					(2.28)				(2.22)	(3.00)
R_EG					0.78 ***				0.78 ***	0.82 ***
					(5.96)				(5.83)	(6.87)
R^2	29	59	65	52	76	60	65	59	76	80
MAPE	0.32	0.21	0.20	0.24	0.15	0.21	0.20	0.22	0.15	0.14
$p(PE = 0)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	138	138	138	138	138	138	138	138	138	138
T	534	534	534	534	534	534	534	534	534	534

Table 6
***War* Mimicking Portfolio and Risk Premium (Cont.)**

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.66 ***	0.45 **	0.26	-0.17	0.36	0.46 **	0.27	0.07	0.31	0.26
	(3.36)	(2.23)	(1.14)	(-0.63)	(1.63)	(2.23)	(1.17)	(0.30)	(1.36)	(1.22)
WMP	-0.87 ***					-0.70 ***	-0.78 ***	-0.90 ***	-0.77 ***	-0.66 ***
	(-2.64)					(-3.34)	(-2.76)	(-2.82)	(-2.90)	(-3.01)
MKT		0.11	0.31	0.76 **		0.10	0.28	0.50		0.32
		(0.38)	(0.98)	(2.23)		(0.33)	(0.90)	(1.54)		(1.10)
SMB		0.14	0.18			0.09	0.09			0.15
		(0.94)	(1.16)			(0.62)	(0.60)			(1.00)
HML		0.31 **				0.28 *				0.49 ***
		(2.01)				(1.84)				(3.23)
RMW		0.18				0.17				0.15
		(1.56)				(1.46)				(1.29)
CMA		0.20 **				0.21 **				0.17 *
		(2.07)				(2.14)				(1.70)
MOM		0.55 ***				0.56 ***				0.39 *
		(2.70)				(2.75)				(1.92)
MGMT			0.46 ***				0.34 **			0.39 ***
			(2.91)				(2.35)			(2.67)
PERF			0.44 **				0.51 **			0.23
			(2.02)				(2.33)			(1.07)
PEAD				0.30 **				0.41 ***		0.37 ***
				(2.03)				(2.88)		(3.31)
FIN				0.58 ***				0.51 **		0.47 **
				(2.92)				(2.53)		(2.41)
R_MKT					0.20				0.25	
					(0.65)				(0.81)	
R_ME					0.31 **				0.23	0.20
					(2.09)				(1.59)	(1.41)
R_IA					0.28 **				0.22 **	0.25 **
					(2.47)				(2.11)	(2.55)
R_ROE					0.22 *				0.20	0.34 ***
					(1.67)				(1.54)	(2.69)
R_EG					0.60 ***				0.59 ***	0.64 ***
					(5.61)				(5.39)	(6.57)
R^2	24	42	43	35	55	43	46	46	57	63
MAPE	0.10	0.09	0.09	0.09	0.08	0.09	0.08	0.08	0.08	0.07
$p(PE = 0)$	0.00	0.00	0.02	0.13	0.71	0.00	0.05	0.45	0.87	1.00
N	1372	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	534	534	534	534	534	534	534	534	534	534

Table 6
War Mimicking Portfolio and Risk Premium (Cont.)

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.67 **	0.95 ***	0.80 ***	1.53 ***	0.67 ***	0.78 ***	0.66 ***	0.62 ***	0.57 ***	0.30
	(2.58)	(6.15)	(5.07)	(7.08)	(3.45)	(5.27)	(4.36)	(3.73)	(3.15)	(1.44)
WMP	-1.34 ***					-1.37 ***	-1.19 ***	-1.82 ***	-0.93 **	-1.47 ***
	(-4.13)					(-4.17)	(-3.91)	(-5.40)	(-2.48)	(-3.91)
MKT		-0.45 *	-0.31	-0.73 ***		-0.25	-0.16	-0.05		0.28
		(-1.74)	(-1.17)	(-2.62)		(-1.01)	(-0.62)	(-0.18)		(0.98)
SMB		0.32 **	0.43 ***			0.16	0.27 *			0.08
		(2.09)	(2.79)			(1.11)	(1.80)			(0.51)
HML		0.31 **				0.27 *				0.49 ***
		(2.10)				(1.84)				(2.87)
RMW		-0.02				0.05				-0.13
		(-0.18)				(0.40)				(-0.93)
CMA		0.84 ***				0.70 ***				0.36 ***
		(7.04)				(6.24)				(2.69)
MOM		0.53 **				0.62 ***				0.54 **
		(2.34)				(2.84)				(2.29)
MGMT			0.65 ***				0.48 ***			0.68 ***
			(3.79)				(2.70)			(3.82)
PERF			0.55 **				0.70 ***			0.85 ***
			(2.26)				(3.06)			(3.65)
PEAD				-0.03				0.61 ***		0.33
				(-0.14)				(3.28)		(1.63)
FIN				0.26				0.56 **		1.18 ***
				(1.15)				(2.53)		(4.62)
R_MKT					-0.08				0.02	
					(-0.29)				(0.09)	
R_ME					0.35 **				0.29 **	0.22
					(2.28)				(1.96)	(1.47)
R_IA					0.42 ***				0.34 **	0.69 ***
					(2.61)				(2.16)	(4.58)
R_ROE					0.17				0.21	0.82 ***
					(0.92)				(1.19)	(4.69)
R_EG					1.47 ***				1.41 ***	1.69 ***
					(8.06)				(7.43)	(10.77)
R^2	33	41	43	13	57	44	45	45	57	65
MAPE	0.16	0.14	0.14	0.19	0.12	0.14	0.14	0.14	0.12	0.11
$p(PE = 0)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	904	904	904	904	904	904	904	904	904	904
T	534	534	534	534	534	534	534	534	534	534

Table 6
War Mimicking Portfolio and Risk Premium (Cont.)

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	-0.04	3.35 ***	3.26 ***	4.19 ***	2.11 ***	-0.18	1.41 ***	0.70 *	1.33 **	0.39
	(-0.11)	(6.80)	(7.47)	(5.99)	(2.74)	(-0.43)	(4.19)	(1.80)	(2.55)	(0.50)
WMP	-2.50 ***					-4.61 ***	-2.88 ***	-2.90 ***	-1.69 **	-0.78
	(-4.85)					(-5.65)	(-5.46)	(-6.84)	(-2.31)	(-0.69)
MKT		-3.39 ***	-3.25 ***	-3.83 ***		0.32	-1.30 ***	-0.70		-0.29
		(-6.11)	(-6.43)	(-5.45)		(0.70)	(-3.39)	(-1.52)		(-0.37)
SMB		0.17	0.11			-0.46 **	-0.45 ***			0.02
		(1.00)	(0.59)			(-2.48)	(-2.80)			(0.10)
HML		1.31 ***				0.78 ***				0.58
		(6.32)				(3.45)				(1.41)
RMW		0.21				1.22 ***				0.53
		(1.00)				(5.53)				(1.38)
CMA		0.30 **				-0.39 *				0.46
		(1.96)				(-1.66)				(1.58)
MOM		0.18				0.72 ***				0.81 **
		(0.76)				(2.83)				(2.34)
MGMT			1.34 ***				0.83 ***			-0.11
			(7.23)				(3.77)			(-0.25)
PERF			0.03				0.43			1.28 *
			(0.09)				(1.52)			(1.72)
PEAD				-0.53 **				-0.06		0.57
				(-2.07)				(-0.25)		(0.87)
FIN				0.77 **				1.80 ***		2.96 ***
				(2.26)				(6.92)		(3.38)
R_MKT					-1.79 **				-0.98 *	
					(-2.21)				(-1.78)	
R_ME					-0.20				-0.30	0.08
					(-0.87)				(-1.36)	(0.29)
R_IA					0.26				0.13	0.16
					(1.02)				(0.53)	(0.44)
R_ROE					-0.19				0.03	1.66 **
					(-0.48)				(0.08)	(2.52)
R_EG					3.37 ***				3.01 ***	4.66 ***
					(5.96)				(6.75)	(6.00)
R^2	31	41	40	34	58	52	45	47	59	85
MAPE	0.61	0.49	0.49	0.54	0.45	0.45	0.47	0.48	0.45	0.25
$p(PE = 0)$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.85
N	360	360	360	360	360	360	360	360	360	360
T	534	534	534	534	534	534	534	534	534	534

Table 7
Three-Pass Test

This table presents the results from the three-pass test of Giglio and Xiu (2021). λ is the factor risk premium estimate (in percentages); R^2_{TS} (in percentages) 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 (2020) 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	-0.26 **	-0.28 *	0.07	0.31 **	0.47 **	0.23 **	0.24 ***	0.36 ***	0.44 ***	0.12 *	0.54 ***	0.23 ***	0.24 **	0.23 ***
t	(-2.26)	(-1.92)	(0.59)	(2.33)	(2.44)	(1.97)	(2.76)	(2.97)	(2.71)	(1.92)	(3.27)	(2.85)	(2.06)	(3.19)
R^2_{TS}	21	42	71	73	87	74	67	74	64	33	76	60	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	-0.20 **	-0.11	0.13	0.21 *	0.48 ***	0.10	0.16 **	0.17	0.28 *	0.08	0.28 *	0.15 *	0.16	0.10
t	(-2.29)	(-0.49)	(1.05)	(1.73)	(2.68)	(0.99)	(1.97)	(1.45)	(1.92)	(1.51)	(1.77)	(1.93)	(1.56)	(1.47)
R^2_{TS}	20	99	79	72	89	72	64	72	64	32	73	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	-0.57 ***	0.51 **	0.12	0.42 ***	0.46 ***	0.07	0.32 ***	0.51 ***	0.20	0.13 **	0.52 ***	0.30 ***	0.10	0.20 **
t	(-4.62)	(2.18)	(0.83)	(3.23)	(2.77)	(0.59)	(3.92)	(4.22)	(1.10)	(1.99)	(3.20)	(4.03)	(0.88)	(2.39)
R^2_{TS}	27	99	92	76	82	64	58	77	57	27	76	55	67	42
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 7
Three-Pass Test (Cont.)

Panel D: ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	WMP	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
λ	-0.45 ***	0.56	-0.15	0.21	0.96 ***	0.57 ***	0.03	0.16	0.72 ***	0.07	0.78 ***	0.11	0.68 ***	0.32 ***
t	(-2.88)	(1.52)	(-1.02)	(1.44)	(4.57)	(5.04)	(0.24)	(0.96)	(4.00)	(0.84)	(3.80)	(0.93)	(6.51)	(3.45)
R^2_{TS}	26	98	89	61	82	54	52	64	52	25	69	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	-0.26 ***	-0.28 **	0.10	0.26 *	0.57 ***	-0.01	0.23 ***	0.28 **	0.27	0.13 **	0.31 *	0.20 **	0.05	0.11
t	(-2.63)	(-2.05)	(0.77)	(1.87)	(2.79)	(-0.12)	(2.67)	(2.25)	(1.58)	(2.14)	(1.66)	(2.42)	(0.46)	(1.53)
R^2_{TS}	22	33	59	73	82	55	65	69	60	30	76	60	60	44
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	-0.38 ***	0.00	0.17	0.29 ***	0.54 ***	0.18 *	0.19 ***	0.28 ***	0.35 **	0.07	0.44 ***	0.18 ***	0.18	0.12 **
t	(-4.43)	(0.02)	(1.37)	(3.11)	(3.04)	(1.76)	(3.34)	(3.04)	(2.23)	(1.31)	(2.99)	(3.41)	(1.64)	(2.02)
R^2_{TS}	24	92	68	53	79	52	50	66	50	21	67	49	54	37
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