War Discourse and the Cross-Section of Expected Stock Returns*

David Hirshleifer† Dat Mai‡ Kuntara Pukthuanthong§

February 2023

Abstract

We test whether a war-related factor model derived from textual analysis of media news explains the cross-section of expected asset returns. The war risk factor is motivated by, and builds on a semi-supervised topic model to extract discourse topics from 7,000,000 New York Times stories spanning 160 years, which has been shown to be powerful in predicting aggregate market returns. We find that war risk factors help predict the cross section of returns across a diverse range of testing assets, deriving from both traditional and machine learning construction techniques, encompassing both public and own-constructed sources, and spanning a wide range of 138 anomalies. These findings are consistent with assets that have poor returns during periods of heightened war risk earning higher risk premia, or alternatively, that a factor based upon war sensitivity captures investor mispricing of war risk. The return premium associated with the war factor is incremental to factors from prominent factor models and other measures of news-based uncertainty. Our results are further buttressed through the factor mimicking portfolio of war risk. War risk passes the protocol of factor identification and is shown to be a genuine risk factor.

*Our *War* index is available from the author's website at https://www.kuntara.net. Software and code to reproduce the results in this paper are available on request.

†University of Southern California, Email: hirshlei@marshall.usc.edu
‡University of Missouri-Columbia, Email: datmai@mail.missouri.edu
§University of Missouri-Columbia, Email: pukthuanthongk@missouri.edu

1 Introduction

The rare disaster risk may explain long-standing asset-pricing questions, such as the equities premium and volatility puzzles, which have generated increased attention in recent years. The frequency and magnitude of rare disasters are crucial to calibrate the rare disaster risk models. Studies have resurrected Rietz (1988)'s initial "catastrophe" justification for the equity premium. Barro (2006) measures the size and frequency of disasters over the 20th century from the gross domestic product (GDP) declines caused by World War I, the Great Depression, and World War II in many nations. He shows, given appropriate calibrations, they are significant enough to provide a substantial equity premium. Gourio (2008)'s model of time-varying catastrophe risk delivers similar outcomes. Gabaix (2012) expands the Barro-Rietz model by including cross-sectional and time-series variance in the projected catastrophe loss. Wachter (2013) extends the Barro-Rietz model by including a time-varying probability of rare disasters and shows that her model can explain the high equity premium and high volatility in the stock market while yielding a low mean and volatility for the government bill rate. The explanation of equity premium due to rare disaster risk leads to a natural cross-sectional implication: assets like gold that perform well during natural disasters should have low average (or predicted) returns. Our study aims to test this conclusion.

Along with the empirical evidence of expected return variations such as (1) small stocks earn higher returns than large stocks on average, (2) value stocks earn higher returns than growth stocks on average, and this effect is more pronounced among small stocks, and (3) stocks which went up recently (winners) earn higher returns than past losers on average–the momentum anomaly, can war exposure explain these asset pricing conundrums as a risk measure? We endeavor to respond to this inquiry.

Although the theory about disaster risk is established, the investigation expedition still faces some obstacles, mainly due to imperfect disaster risk measures. Individual nations seldom experience major disasters, which impedes the empirical testing of rare disaster models. 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). The challenge of empirical verification is substantial because calibrations based on catastrophe models are very sensitive to underlying assumptions.

Even if most of these crises did not evolve into a full-scale war or significant conflict, the forward-looking nature of financial market pricing enables us to determine the influence of changes in the likelihood of uncommon catastrophes on stock market prices. As a result, although previous research infers the presence of a disaster risk premium from asset prices, we explicitly examine whether a correlation exists between changes in disaster risk and stock market price fluctuations. Our analysis circumvents the issue of a limited sample size embedded in the use of actual rare disasters by concentrating on a much larger sample of possible rare disasters: attention to war risk.

Our approach is based on Hirshleifer, Mai, and Pukthuanthong (2023), who construct war risk topics (hereafter, *War*) from *the New York Times* (*NYT*) since its inception in the 1880s. They apply a novel semi-supervised topic modeling method (sLDA) to extract topics from news. The sLDA allows them to perform a rolling estimation using the information available only then. This allows them to avoid any forward-looking bias, a core issue of asset return predictability. In addition, the technique allows them to adjust their semantic changes over time. News is an excellent instrument to construct war risk. First, it presents market attention to war risk, which captures current expectations. Editors cater news to their audience. Our war risk complies with Merton (1973)'s ICAPM spirit. Merton (1973) contends that state variables that capture future investment opportunities should impact the agents current consumption. Such state variables present fundamental risks; hence, assets that covary with such state variables should command a risk premium. Our war risk fits this notation.

Our war risk has a daily frequency and high variation that match stock returns, thereby, we address the drawback of macro variables, which are known for being stale and having low frequency. In theory, macroeconomic variables are good proxies for state variables (Cochrane, 1996); they do not perform empirically due to their data limit. Our measure presents an alternative proxy of state variables filling these gaps.

An extended data series like ours of 180 years is essential for inferring cross-sectional asset pricing tests. We construct war risk as a shock and its traded version by factor mimicking portfolios. We apply Pukthuanthong, Roll, and Subrahmanyam (2019)'s protocol of factor identification comprising two conditions: the necessary condition testing whether factors are related to the covariance of returns and the sufficient condition testing whether candidate factors that pass the necessary condition can price assets cross-sectionally. Pooling all candidate factors from all seminal factor models together with the War factor, we find *War* factor survives both conditions; thus, it is a genuine priced risk factor.

Testing assets play a crucial role in cross-sectional asset pricing test (Giglio, Xiu, and Zhang (2021)). The low dimensionality of testing assets favors the factors constructed by corresponding characteristics Lewellen, Nagel, and Shanken (2010)). To address these concerns, we employ a large collective set of testing assets that span multi-dimensions of characteristics based on sorting and machine learning construction, and collected from public sources and constructed by us: (1) 138 long-short anomalies from Hou, Xue, and Zhang (2020) (hereafter, HXZ), (2) 1372 single-sorted portfolios from HXZ, (3) 360 machine learning based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020), (4) our own constructed 128 anomalies to replicate the first set, and (5) our own constructed 2190 nonlinear portfolios.[1]

Interestingly, *War* best prices Bryzgalova, Pelger, and Zhu (2020)'s machine learning-based nonlinear portfolios (hereafter, ML-based nonlinear portfolios). *War* as a solo factor model outperforms some prominent factor models with an R^2 of 43% when the test assets are the ML-based nonlinear portfolios. When *War* is added to the multifactor benchmarks, the average cross-sectional pricing error or intercept is reduced significantly from 3% to almost zero percent. *War* as a sole factor generates the lowest and most insignificant standard pricing error compared to other benchmarks (0.4% vs. 3%). *War* has the largest and most significant cross-sectional prices of risk with a magnitude of -33% when pricing ML-based nonlinear portfolios, compared to -17% when pricing anomalies and -8% when pricing single-sorted portfolios. Bryzgalova, Pelger, and Zhu (2020) show that ML-based nonlinear portfolios capture the complex interactions among many characteristics and the nonlinear impact of characteristics on returns. They span the SDF, are more challenging to price than conventional cross-sections, and generate the highest possible Sharpe ratio out-of-sample. *War* seems to possess a unique property that prices these assets very well. We leave it for future research to investigate further.

Our result supports the disaster risk theory asserting that assets providing returns during high war risk periods perform like a hedging asset and command negative risk premium.

Within the literature on disaster risks and news, Manela and Moreira (2017) (henceforth, MM) applies a machine learning approach to construct a news-based measure of uncertainty from the front page of *WSJ* from 1890, called NVIX and Caldara and Iacoviello (2022) constructs uncertainty index from news using dictionary approach. We control their measures,

[1]The data is publicly available from the author's website.

and our War factor is distinct. Our risk premium is still negative and significant, not being subsumed by either of these measures. See (Hirshleifer, Mai, and Pukthuanthong, 2023) for the detail of our differences from these measures.

Notably, we are the first study examining whether an empirical measure of rare disaster risks captured by *War* demands a significant risk premium. Gabaix (2012) and Gourio (2008) argue that assets that provide high returns during a high disaster risk period should perform as a hedging asset and thus have lower expected returns. To test this argument, we use innovations in *War* as a factor and perform a robustness test using factor-mimicking portfolios. Both forms of the *War* factor confirm that *War* prices 118 anomalies and 1173 characteristics-sorted portfolios. It demands a negative price of risk: assets that pay off during war times are good hedges and demand lower expected returns.

In this paper, we deepen our understanding of war risk. We enhance Hirshleifer, Mai, and Pukthuanthong (2023), who show *War* predicts stock and bond returns out of sample. This study shows that the *War* factor can explain stock returns cross-sectionally. While, to our knowledge, no prior study has attempted to evaluate the catastrophe model using the cross-section of average stock returns, a few studies do analogous empirical exercises. First, several studies examine the imbalance between upside and adverse risk. According to Ang, Hodrick, Xing, and Zhang (2006), the downside risk is more significant than the upside risk. They do not, however, differentiate between high downside risk and modest downside risk. War risks are distinct from the downside beta studied by Ang, Hodrick, Xing, and Zhang (2006) and jump beta studied by Cremers, Halling, and Weinbaum (2015) because our measures are exposed to changes in the probability of future bear market states. In contrast, downside beta and jump beta are sensitivities to present realizations of downside market states and jumps, respectively. Our measure differs from the volatility beta investigated by Ang, Hodrick, Xing, and Zhang (2006), Chang, Christoffersen, and Jacobs (2013), and Cremers, Halling, and Weinbaum (2015) because war risk concentrates on left-tail outcomes. The significance of these discrepancies has been emphasized in both theoretical (Gabaix (2012); Wachter (2013)) and empirical (many time-series studies) research (Santa-Clara and Yan (2010); Bollerslev and Todorov (2011); Christoffersen, Jacobs, and Ornthanalai (2012); Andersen, Fusari, and Todorov (2015); Hirshleifer, Mai, and Pukthuanthong (2023)).

Our measure is also distinct from Lu, Ott, Cardie, and Tsou (2011)'s bear beta constructed from the S&P500 index option. While Ang, Hodrick, Xing, and Zhang (2006)'s downside beta analyzes how the price of a stock responds when a conflict happens. Lu and Murray (2019)'s bear beta captures the likelihood of a future conflict, and the bear market risk increases, even if a war does not occur. Our measure of *War* risk captures both as it is based on news, which captures the realization and the market expectation. In short, *War* risk includes time dimensions captured by downside and bear betas.

Specific stock prices will respond more strongly than others to the rise in war risk. Noting that the market portfolio is made of all stocks and is thus vulnerable to the same sources of risk as individual stocks, including war risk. It is vital to highlight that the price of the market portfolio will likewise respond. We account for this impact by including the market excess return into the two-pass regression to estimate the price of *war* risk. If a stock's response to *War* risk is reflected by its exposure to the market portfolio, then this stock will have a *War* beta of zero. *War* betas sustain and are nonzero for stocks with greater or lesser exposure to *War* market risk than the market portfolio.

Lastly, Gourio (2008) develops a theory to explain the pricing ability of war risk cross-sectionally and conducts the test. He could not find a significant risk premium and admits this is due to a poor estimator of disaster risk. (Berkman, Jacobsen, and Lee, 2011) also test whether war risk prices the Fama-French 30 industry portfolios after controlling for the Fama-French three-factor model. We differ by considering a more extensive set of test assets and benchmarking our results against all leading factor models.

2 Method

This paper uses the sLDA model (Lu, Ott, Cardie, and Tsou, 2011) to extract news narratives. In this section, we briefly discuss the setup of the model and our implementation.

2.1 Model

This paper uses a probabilistic topic model to extract latent topic weights from news articles. Topic models are developed based on the core idea that documents are mixtures of topics in which each topic is a probability distribution over words (Blei, 2012; Steyvers and Griffiths, 2007). Under topic models, we assume that text documents are generated according to a generative process. To make a new document, one first chooses a distribution over topics (i.e., document-topic distribution). Then for each word in the document, one picks a topic randomly from this document-topic distribution and subsequently draws a word from that topic using its distribution over words (i.e., topic-word distribution). In this setup, the document-topic distribution for each document, topic-word distribution for each topic (the same across documents), and topic assignment for each word are unobserved variables that can be inferred from the observable word frequencies in the document collection. In other words, we can use standard statistical techniques to revert the generative process, inferring the topics responsible for generating a collection of documents (Steyvers and Griffiths, 2007).

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

- The word weight vector ϕ_k of topic k follows a prior Dirichlet distribution governed by parameter β: $\phi_k \sim \text{Dirichlet}(\beta)$.[2]
- The topic weight vector θ_d of document d follows a prior Dirichlet distribution governed by parameter α: $\theta_d \sim \text{Dirichlet}(\alpha)$.[3][4]
- For each word w in document d, we
    - randomly select from a topic from the document-topic distribution:

[2] For illustration, assume a topic k has three words: $word_1$, $word_2$, and $word_3$ with the weights given to the three words capturing by $\phi_k = [w_1, w_2, w_3]$ with $w_1 + w_2 + w_3 = 1$. The model assumes that this ϕ_k vector follows a Dirichlet distribution. The random variable here is the vector of weights representing the words in the topic. If a topic has $word_1$, $word_1$, $word_1$, $word_2$, $word_2$, then $word_3$, w_1=0.5, w_2=0.333, and $w_3 = 0.17$. These are all unobserved and must be estimated from sampling from the posterior distribution.

[3] Similarly, assume document d has four topics $topic_1$, $topic_2$, $topic_3$, $topic_4$ with the weights given to these topics captured by $\theta_d = [w_1, w_2, w_3, w_4]$ with $w_1 + w_2 + w_3 + w_4 = 1$. The model assumes that this θ_d vector follows a Dirichlet distribution. The random variable here is the vector of weights representing the topics in the document. The weights are calculated from the samples drawn from the posterior distribution of the model. Based on these assignments, we generate topic assignments for all words via sampling from the posterior and compute the word weights ϕ_k and topic weights θ_d. We iteratively do this until the convergence of the posterior distribution.

[4] In the univariate case, assume that the distribution is binomial. For each trial, the success rate is p, which is the parameter of the binomial distribution. In Bayesian statistics, we assume that the parameter p follows the Beta distribution. We can generalize this to the multivariate case. Instead of just success (p) and failure (1-p), we have multiple classes; thus, p is a vector. In Bayesian statistics, we assume p follows a Dirichlet distribution (a generalization of Beta). As a simple example, in a jar, there are three types of marbles red, blue, and green, with the probability of p_1, p_2, and p_3. The number of marbles of each type thus follows the multinomial distribution characterized by the parameter p=[p_1, p_2, p_3]. In frequentist, we directly estimate p = [p_1, p_2, p_3] with our data. In Bayesian, we assume that p = [p_1, p_2, p_3] follows a Dirichlet distribution. We then multiply the multinomial and Dirichlet distribution by computing the posterior distribution and estimating its p vector.

$z_{d,w} \sim \text{Multinomial}(\theta_d)$, then

– randomly select from a word from the previously selected topic:
$w \sim \text{Multinomial}(\phi_{z_{d,w}})$.

In this setup, the topic-word distribution ϕ_k, document-topic distribution θ_d, and topic assignment $z_{d,w}$ are three latent parameters we want to estimate.

Among the three, document-topic distribution θ_d is of utmost interest because it summarizes the attention allocated to each topic in each news article. To estimate these parameters using a Bayesian method, Griffiths and Steyvers (2004) specifies that ϕ_k and θ_d follow two Dirichlet distributions (these two are referred to as the "prior" distribution in Bayesian statistic). From these specifications, we can derive the distribution of the topic assignment $z_{d,w}$ conditioned on observed word frequency (this conditional distribution is referred to as the "posterior" distribution). We then use Gibbs sampling to simulate this posterior distribution and estimate the three hidden model parameters.[5]

Users of the traditional unsupervised LDA developed by Blei, Ng, and Jordan (2003) and Griffiths and Steyvers (2004) only need to pre-specify the number of topics K and let the model cluster words into these topics based on word frequencies in a completely unsupervised manner. Specifically, the LDA model is more likely to assign a word w to a topic k in a document d if w has been assigned to k across many different documents and k has been used multiple times in d (Steyvers and Griffiths, 2007). Because the model uses a probabilistic process to uncover underlying topics, users of LDA have no control over topic assignments.

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

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

where V is the corpus or text collection, $C_w > 0$ when w is a seed word in topic k and $C_w = 0$ when w is not a seed word. Intuitively, sLDA gives preference to seed words w in topic k in the form of pseudo count C_w and clusters words into topics based on their co-occurrences

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

with the seed words. Notably, when a seed word is absent in a text collection by design, it does not enter the sLDA model or impact the estimation process.

2.2 Seed Words

The foundational piece of an sLDA model is the set of seed words representing the prior knowledge of each topic. Watanabe and Zhou (2020) emphasize that a dictionary of seed words needs to be carefully chosen based on field-specific knowledge independent of word frequencies in the text collection. **??** lists the lemmatized[6] seed words for each narrative. Our seed words for *War* include *conflict, tension, terrorism, war* and seed words for Pandemic include *epidemic, pandemic*. Notably, the seed words need to be general fundamental concepts that can have reasonably stable meanings over very long periods. Our methodology allows for the fact that the meanings of other words (such as "nuclear") may evolve or may even be neologisms that do not exist early in the sample.[7]

The seed words for the non-disaster-focused narratives are manually collected from Shiller (2019). These words are italicized and discussed extensively in Shiller (2019). We also add certain words that help define the themes of the narratives. We want to emphasize that we remove any words that we are only introduced recently, such as *bitcoin*, *machine learning*, or *great recession*, in selecting the seed words to avoid any look-ahead bias. As shown in **??**, we have reclassified the nine narratives from Shiller (2019) into 12 topics to facilitate our estimation specifically, as *Panic* and *Confidence* are opposing notions, we split them into two topics. Similarly, *Frugality versus Conspicuous Consumption* is split into *Frugality* and *Conspicuous Consumption*. We further divide *Real Estate Booms and Bursts* into two separate topics, namely *Real Estates Booms* and *Real Estates Bursts*. In addition to *Stock Market Bubbles*, we add *Stock Market Crashes*. In contrast, because of their similarities, we combine *Labor Saving Machines* and *Automation and Artificial Intelligence* into one topic.

In a semisupervised topic model such as sLDA, the best approach to examine if the number of topics is reasonable is to investigate the most common terms within a topic post-estimation to determine whether the topics feature the desired contents (Lu, Ott, Cardie, and Tsou, 2011; Watanabe and Zhou, 2020). In addition to the 14 topics discussed above, we

[6] Lemmatization means removing word endings such as *s, es, ing, ed,* etc.

[7] In tracking the articles making the most significant contribution to *War* over the past 30 years, we find that all of them feature wars, terrorism, and tensions in international relations.

include one additional "garbage collector" to absorb everything unrelated to these narratives in the news.[8]

2.3 Estimation

Figure 1 illustrates the rolling estimation scheme used in the paper. Specifically, 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.[9] Notably, rolling estimation is viable only under the sLDA model because we can ensure the consistency of thematic contents over time using seed words.

During each estimation, we draw 200 samples from the posterior distribution of the sLDA model and use the last draw to estimate the document-topic weights θ_d; that is, we estimate a different 14×1 vector $\theta_d = [\theta_d^1, \theta_d^2, \ldots, \theta_d^{14}]$ for each news article, d, in the estimation window.[10] We then compute the monthly weights of each topic i ($i = 1, 2, \ldots, 14$) as the average weight of each topic across all articles in month t, weighted by the length of each article:[11]

$$\theta_t^i = \frac{\sum_{d=1}^{n_t} \theta_d^i \times length(d)}{\sum_{d=1}^{n_t} length(d)}, \tag{2}$$

where θ_t^i is the weight of topic i in month t, n_t is the total number of news articles in month t, and $length(d)$ is the total number of unigrams (one-word terms), bigrams (two-word terms),

[8]When we use many topics, the weights of seeded topics can be approximated by the frequency of the seed words in the corpus. We investigate this case by constructing topic weights as the counts of seed words scaled by the article's length and present the results in Internet Appendix **??**. We report that frequency-based topic weights still yield results consistent with the sLDA ones, yet their out-of-sample performance is weaker.

[9]Estimation is implemented by the seededla package in R and runs on a high-performance computing (HPC) cluster. Full estimation of the model parallelized on 80 computational nodes requires about one week. Following standard practice, we set $\alpha = 50/K$ where K is the number of topics, $\beta = 0.1$, and $C_w = 0.01$ for seed word w.

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

[11]Equal weighting of topic weights across articles yields similar results.

and trigrams (three-word terms) in article d.[12]

Although ten years of news articles are used to estimate the model, 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 narratives. These time series will be used as input into our economic forecasting applications.

Our method takes the evolution of word usage into account. Although the list of seed words remains unchanged, the model is re-estimated monthly using data for the past ten years (including the current month), so the actual words clustered in the topics change monthly. The list of "unobserved" words (from the model's output) varies monthly based on language changes.

Notably, topic modeling is more about examining the thematic content as a whole and less about picking up on each word belonging to the topic. For instance, terms such as *state* and *government* also show up in our *War* topic and by themselves are not tension-related words. However, in the context of other words showing up with them in *War*, these terms are an integral part of a topic on wars and international tensions. In other words, we cannot talk about global tensions without mentioning *state* and *government*.

3 Data

We leverage the richness of full newspaper texts using all articles since the beginning of the *NYT*'s inception; however, we still remove articles with limited content, such as those that contain mostly numbers, names, or lists. Then we conduct the standard text processing steps.[13]

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 previous section.

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

[13] Please refer to Internet Appendix A of Hirshleifer, Mai, and Pukthuanthong (2023) for details on our text cleaning process.

Panel A of Figure 2 plots the time series of monthly article counts after excluding articles with limited content. Since 1871, the *NYT* has published over 6.8 million news articles with an average monthly of 3,800.[14]

Panel B of Figure 2 reports the average monthly article length, which is defined as the total count of unigrams (one-word terms), bigrams (two-word terms), and trigrams (three-word terms). While Bybee, Kelly, Manela, and Xiu (2021) consider only unigrams and bigrams in their paper, we extend the analysis to trigrams as a majority of the seed words have three words, such as *real estate boom, stock market bubble*, and *cost push inflation*. Over 1871–2019, articles come in at an average length of 493 ngrams.

4 Textual Discourse about *War* Risk

This section examines the evolution of various topics over time, with particular emphasis on the war index, *War*. Apart from *War*, our topics exhibit no clear time trends; we therefore focus our discussion on the time series of *War*. Figure 4 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. The War index 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. It peaked in 1963 with President John F. Kennedy's assassination.

Hirshleifer, Mai, and Pukthuanthong (2023) find that the predictive power of *War* for the aggregate stock market has become more pronounced in recent decades. Consequently, we focus on the last 30 years of the sample, examining the ten articles with the most significant contributions to the ten highest monthly scores of War hikes since 1990. Figure 5 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's climate of international tensions, including the nuclear weapons development and tests by North Korea. A detailed description of the statistics for all extracted topics are provided in Hirshleifer, Mai, and Pukthuanthong (2023).

[14] Data are missing for September, and October 1978 (due to strikes) and thus are excluded from Figure 2.

5 *War* Discourse and the Cross-Section of Expected Returns

Hirshleifer, Mai, and Pukthuanthong (2023) document that *War* is a positive predictor of the aggregate stock market return. This section tests whether *War* can be used to predict the cross section of expected stock returns. Specifically, we test whether loadings on a factor based on war are positive return predictors.

Such a relationship is implied by models of rare disaster risks (Barro, 2006; Barro, 2009) as discussed in Gourio (2008). In such a setting, stocks that provide high returns during periods of high *War* risk provide a hedge for aggregate consumption and therefore command low risk premia. Alternatively, at least two behavioral hypotheses offer a similar implication. The first hypothesis is that investors overweight the risk of war because of its high salience. The second is that if investors have cumulative prospect theory preferences, there is overweighting of low probabilities, so rare risks in general (including the risk of war) are overweighted.

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, such as that used in Gourio (2008), have limited sample size for the occurrence of rare events. Low small sample size reduces power to identify the asset pricing consequences of extreme events.[15] 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 the cross-section of asset returns using a linear factor model and the data from July 1972 to December 2016.[16] There are both rational factor pricing and behavioral theories for why loadings on the *War* factor may positively predict returns.[17] Under rational factor pricing, investors require a risk premium for bearing greater war risk (beyond the standard CAPM premium for beta), perhaps because of a stochastically

[15] 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 on average and over time have low average returns, and industries that did poorly (e.g., transportation, aerospace, cars, leisure) should on average have high returns.

[16] Our sample is constrained by data availability of different risk factors.

[17] **hirshleifer/jiang:07** and Daniel, Hirshleifer, and Sun (2020) discuss why loadings on behavioral factors in general are proxies for mispricing, and are therefore cross-sectional return predictors.

varying investment opportunity set.

Under the behavioral theory, investors overweight war risk, perhaps because rare disasters are highly salient (resulting in overestimation of their probability) or because investors have a cumulative prospect theory value function wherein small probabilities are overweighted. When war risk is overweighted, stocks that are highly negatively sensitive to war risk (i.e., will do poorly in the event of war) will be undervalued relative to stocks that are less negatively sensitive (or are positively sensitive). A long-short portfolio that buys the undervalued stocks and sells the overvalued stocks (i.e., a war factor) will earn a positive return premium. Stocks with higher (more positive) loadings on the war factor will be more undervalued by investors. Such stocks are highly sensitive to the war risk that investors are pessimistic about. Such stocks will therefore earn higher expected returns than stocks with low loadings.

To capture rational factor pricing, we propose an SDF for excess returns that are affine in the *War* factor (henceforth, *WarFac*):

$$SDF_t = 1 - b \times WarFac_t. \tag{3}$$

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

$$\begin{aligned} 0 &= \mathbb{E}\left[R^e_{i,t} SDF_t\right] = \mathbb{E}\left[R^e_{i,t}\right]\mathbb{E}[SDF_t] + \text{cov}\left(R^e_{i,t}, SDF_t\right) \\ &= \mathbb{E}\left[R^e_{i,t}\right]\frac{1}{R_f} - b \times \text{cov}\left(R^e_{i,t}, WarFac_t\right), \quad \text{or} \\ \mathbb{E}\left[R^e_{i,t}\right] &= R^f b \text{var}\left(WarFac_t\right) \times \frac{\text{cov}\left(R^e_{i,t}, WarFac_t\right)}{\text{var}\left(WarFac_t\right)}, \\ \mathbb{E}\left[R^e_{i,t}\right] &= \lambda_{War} \times \beta_{i,War}, \end{aligned} \tag{4}$$

where $R^e_{i,t}$ is the excess return of asset i at time t, $\beta_{i,War} = \frac{\text{cov}\left(R^e_{i,t}, WarFac_t\right)}{\text{var}(WarFac_t)}$ denotes the exposure of asset i to the *War* factor, and λ_{War} is the cross-sectional price of risk associated with the *War* factor. Alternatively, the behavioral interpretation of λ is that it measures the extent to which assets with higher sensitivity to war risk are undervalued relative to stocks that have lower war-risk sensitivity.

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

$$R^e_{i,t} = c_i + \beta'_{i,f} f_t + \epsilon_{i,t}, \tag{5}$$

where f_t presents a vector of risk factors. Then, to estimate the cross-sectional price of risk or risk premium 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:

$$\mathbb{E}\left[R^e_{i,t}\right] = \mu_{R,i} = \alpha + \beta'_{i,f}\lambda_f + e_i \quad \text{for } i = 1, \ldots, N. \tag{6}$$

We then obtain estimates of the cross-sectional return premium slope λ and the average cross-sectional pricing error or zero-beta rate, α. Under rational factor pricing, the intercept (α) is predicted to be economically and statistically insignificant. Under either rational factor pricing or behavioral pricing theories, the return premium slope (λ) should be statistically significant, economically substantial, and stable across different cross sections of test assets. We report the t-statistics computed with the Shanken (1992)'s corrected standard errors. The variable e_i captures the pricing error, which is predicted to be zero under rational factor pricing. To measure the size of pricing errors, we report the cross-sectional $R^2 (= 1 - \sigma^2_e / \sigma^2_{\mu_R})$. Under rational factor pricing, the R^2 should be 1, so the estimated R^2 measures how well the model fits the data.

Following He, Kelly, and Manela (2017), we construct our *War* factor, denoted as $WarFac_t$, as the innovation from an AR(1) model of *War* and test its pricing ability. 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*:

$$War_t = \rho_0 + \rho \times War_{t-1} + u_t \quad \text{and} \tag{7}$$

$$WarFac_t = \frac{u_t}{War_{t-1}}. \tag{8}$$

This is the *War* factor that we will use in the cross-sectional tests.

We consider a large set of test assets constructed from a wide range of characteristics,[18] including:

[1] 138 long-minus-short anomalies from Hou, Xue, and Zhang (2020) (hereafter HXZ),

[2] 1372 single-sorted portfolios from HXZ,

[3] 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020),

[4] Our own constructed 128 anomalies based on HXZ,

[18] Lewellen, Nagel, and Shanken (2010) shows 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.

[5] Our own constructed 2190 non-linear portfolios.[19]

We test whether War is an economy-wide factor that help explains a wide range of anomalies. Thus we include a variety of testing assets, both traditional and complex.[20] We start with test assets based on anomaly characteristics, including the 138 anomalies from HXZ: momentum, value versus growth, investment, trading frictions, intangibles, and profitability. Second, to span a large return space, we include all their 1372 single-sorted portfolios available from 1967 to 2016. Third, we replicate HXZ and construct our anomalies. We use them as another set of testing assets for a robustness check. Fourth, we build non-linear portfolios based on three polynomials. See Appendix C.2 for a description of how these anomalies are constructed. Finally, we include the 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 argue that the ML-based nonlinear portfolios present a new way of building better cross-sections of portfolios that can be used in structural and reduced-form models.

Next, we examine the pricing effectiveness of $WarFac_t$ as compared with the factors in several well known factor models such as the Fama-French six-factor model (FF6), Stambaugh and Yuan (2017)'s mispricing factor model (M4), Daniel, Hirshleifer, and Sun (2020)'s composite behavioral and rational factor model (DHS), and Hou, Mo, Xue, and Zhang (2021)'s q-factor model (Q5). $WarFac_t$ increases the model fit of each these factor models by 13%, 11%, 19%, and 7%, respectively. The testing assets that $WarFac_t$ best prices are the anomaly characteristics and the ML-based nonlinear portfolios. $WarFac_t$ as a single factor prices these assets with a much higher R^2 of 42%.

We test the performance of $WarFac_t$ on various sets of test assets, beginning with the 138 anomaly characteristics from HXZ. , We examine the performance of $WarFac_t$ on its own, and then test whether introducing $WarFac_t$ as an additional factor to the FF6, M4, DHS, and Q5 factor models provides incremental explanatory power.

Panel A of Table 1 describes the performance of $WarFac_t$ as a single factor model. Starting in the first column with $WarFac_t$ as War factor, the slope of the relation between

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

[20]See Appendix C for the detailed construction and the coverage of our testing assets.

returns and *War* loadings is negative and significant at the 1% level ($t = -2.67$). Its monthly return premium is -17.13%. 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 therefore command a lower risk premium. In a behavioral setting, the negative sign indicates that such assets are overpriced by investors who overweight war risk.

$WarFac_t$ has a monthly standard deviation of 13.6%, so its first-stage betas are much smaller than those produced by traded factors. As a result, the return premium per unit of loading (its price of risk under rational factor pricing) is much larger than that of the other traded factors.

$WarFac_t$ maintains its significance even after the introduction of other factors to the model. The inclusion of FF6 and M4 factors alongside $WarFac_t$ does result in a reduction of 3% in the return premium of *War*. Additionally, when $WarFac_t$ was added to the Q5 factors, the return premium decreases by 9%, and it marginally increased by 0.30% when added to DHS. The introduction of $WarFac_t$ to the FF6 factor model led to an increase in the model's explanatory power (R-squared) by 9%, while its addition to M4, DHS, and Q5 resulted in a respective increase in explanatory power of 5%, 15%, and 2%. When considered as a solo factor, $WarFac_t$ possessed an R^2 of 42%, while FF6, M4, DHS, and Q5 exhibited R^2 values of 59%, 65%, 51%, and 77%, respectively, demonstrating that $WarFac_t$ as a solo factor provides a good model fit.

We next evaluate the performance of $WarFac_t$ in pricing the 1372 single-sorted portfolios as test assets, as shown in Panel B of Table 1. The monthly return premium for *War* is reduced by more than a half, from -17% to -8%, and the absolute t-statistic diminishes from 2.67 to 2.34. This indicates that $WarFac_t$ provides better pricing of the anomalies. Furthermore, the inclusion of $WarFac_t$ in the factor models resulted in an increase of approximately 4% in their explanatory power. However, as a single-factor model, *WarFac* did not price these testing assets and anomalies proficiently, as its R^2 was only 16% in comparison to the higher percentages of 42%, 43%, 34%, and 55% provided by FF6, M4, DHS, and Q5, respectively.

When the test assets are the 360 ML-based nonlinear portfolios, we find that the return premium for loading on *War* risk is of -40% per month, as seen in the first column in Panel C of Table 1. Remarkably, the monthly return premium for loading on *War* risk increases (in absolute magnitude) to become -56%, -45%, -47%, and -44% after including FF6, M4, DHS, and Q5. Furthermore, including $WarFac_t$ enhances the explanatory power (R-squared) of FF6, M4, DHS, and Q5 models by 25%, 18%, 26%, and 9%, respectively. For this set of testing assets, the explanatory power of the $WarFac_t$ as a single-factor model is 43%, which is on par with FF6 and M4 (both at 41%), higher than DHS (38%), and lower than Q5 (58%).

To sum up so far, as with the anomalies test portfolios, $WarFac_t$ is very effective in pricing the HXZ test portfolios, the anomalies test portfolios, and the nonlinear test portfolios. It has strong predictive power both as a solo factor and incremental to the well-known factor models.

To evaluate the robustness of our findings, we perform additional tests using our constructed anomalies and nonlinear portfolios as test assets. Our 104 anomalies are constructed in a similar vein to those in HXZ. We find that $WarFac_t$ provides the most additional information for pricing to DHS, followed by FF6, M4, and Q5. The inclusion of $WarFac_t$ increases the explanatory power (R-squared) by 21%, 15%, 25%, and 7% for FF6, M4, DHS, and Q5, respectively. As a single-factor model, $WarFac_t$ exhibits an R-squared of 30%, which is higher than that of FF6 (23%) and DHS (14%), roughly equivalent to M4, but lower than Q5 (47%).

For our 2190 nonlinear portfolios constructed from the characteristics up to three polynomials (see Appendix for detailed construction), $WarFac_t$ generates an R-squared of 13% with a monthly return premium of about 10%. The inclusion of $WarFac_t$ in FF6, M4, DHS, and Q5 leads to a similar return premium. However, it contributes around 7% to 9% to the explanatory power of FF6, M4, and Q5, and 20% to DHS. The results of these additional test assets are reported in Table A1 in Appendix **??**.

In summary, we find that $WarFac_t$ prices a wide range of test assets, and assets that pay off during high *War* risk periods are either underpriced on average or are good hedges, thereby earning low return premia. We find that $WarFac_t$ prices anomalies and nonlinear assets very well, and it contributes to the explanatory power of the benchmark models by approximately 20% when pricing 360 ML-based nonlinear portfolios and 128 anomalies.

Our findings indicate that *War* is effective in pricing a wide range of assets, including 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 cross-sections. Furthermore, these portfolios span the stochastic discount factor (SDF) and generate the highest possible Sharpe ratio out-of-sample, making them an essential test asset in rational asset pricing.

Interestingly, *War* exhibits a negative return premium for factor loadings that is most significant and largest for the ML-based nonlinear portfolios compared to other testing assets, with a magnitude of -33% compared to -17% for anomalies and -8% for single-sorted portfolios. This result suggests that *War* can capture nonlinear dependencies among characteristics in predicting returns, making it a powerful tool for asset pricing.

Moreover, the addition of *War* to the multifactor benchmark models to price the ML-based nonlinear portfolios substantially reduced the average cross-sectional pricing error or intercept from prominent factor models, from 3.25% to close to zero percent on average.

This finding suggests that *War* is a valuable addition to the set of benchmark models for pricing a diverse range of assets.

6 The *War* Factor-Mimicking Portfolio

Our previous analysis constructs *WarFac* as a shock from the first-order autoregressive process. It is a simple and less computing demanding approach. Nonetheless, it is based on the assumption the relationship between macroeconomic variables and asset prices is linear, which may not be true in reality and it does not account for the impact of other factors that may affect asset prices.

In this section, we form a traded version of the *WarFac* or the War-factor Mimicking Portfolio (WMP) by projecting the *War* factor ($WarFac_t$) onto the space of excess returns. WMP is in the form of a traded return. Compared to the shock, the mimicking portfolios captures the exposure of assets to macroeconomic factors. The drawback is it requires more data and computational resources. The construction of the mimicking portfolio may also be subject to errors due to model misspecification or estimation errors.

We present the results from both the shock and WMP to ensure the results are robust and to address the inflated price of the risk issue.

6.1 Construction of WMP

The return premium for *War* loadings, which we estimate to be around 22% per month across test assets, is economically substantial. Rational asset pricing theory suggests that most non-traded factors exhibit an inflated price of risk owing to the presence of noise and measurement errors that remain uncorrelated with returns. Consequently, such errors tend to compress the variation in beta estimates (see Pukthuanthong, Roll, Junbo, and Tengfei (2022) for the measurement errors of non-tradable asset and remedy). In a similar vein, mispricing factors also tend to compress beta estimates due to measurement error. Adrian, Etula, and Muir (2014) contend that a non-traded factor is a linear combination of the factor mimicking portfolios (FMP) and error, where the FMP represents a projection of the non-traded asset on the return space. To tackle the inflated risk issue of non-traded factors, they advocate for the construction of FMPs and re-performance of tests. This construction process, termed the time-series approach presents a practical solution that not only simplifies the testing process but also provides insights into the potential alpha and Sharpe ratio generated by the War loadings. Therefore, the time-series approach contributes significantly to the practical literature on alpha-seeking strategies.

To construct WMP, we project our nontraded *War* factor onto the space of excess returns,

$$WarFac_t = \alpha + \beta' \left[SL, SM, SH, BL, BM, BH, Mom\right] + \epsilon_t, \tag{9}$$

where (SL, SM, SH, BL, BM, BH, Mom) is the vector of excess returns of the six Fama-French benchmark portfolios on size (Small [S] and Big (B)) and book-to-market (Low(L), Medium(M), and High(H)) over the riskfree rate and Mom is the momentum factor. We follow Adrian, Etula, and Muir (2014), who choose these characteristic portfolios for their ability to span a substantial portion of the return space.[21] We then define WMP as the fitted value,

$$WMP_t = \hat{\beta}' \left[BL, BM, BH, SL, SM, SH, Mom\right], \tag{10}$$

where $\hat{\beta} = [0.66, 0.27, -0.83, -0.18, -0.49, 0.37, -0.10]$ is estimated via OLS from 1967 to 2016. Since we use the full period to estimate this regression, this methodology is subject to look-ahead bias.

[21] Ideally, the error ϵ_t is orthogonal to the space of returns so that the covariance of any asset with $WarFac_t$ is identical to its covariance with the WMP, defined as the fitted value of the regression.

6.2 Pricing Results Using the WMP

We investigate the pricing performance of the factor mimicking portfolio WMP using the same test assets we used in the previous sections to test the performance of $WarFac_t$ and report the results in Table 2. We find that in a single-factor model with WMP, the return premium for loading on war risk is negative across test assets. It is significant at the 1% level for the 118 anomaly characteristic portfolios and the 360 ML-based nonlinear portfolios, weakly significant at the 10% level for the 1173 single-sorted portfolios and for our 2,190 own-constructed nonlinear portfolios, and insignificant for our 104 own-constructed anomaly portfolios. See Section 5 for the layout of the five sets of testing assets we employ in this study. The monthly return premium for loading on the war risk factor WMP is -0.55% for the 118 anomaly characteristic portfolios, -0.24% for the 1,173 single-sorted portfolios, -0.14% for our own-constructed 104 anomaly characteristic portfolios, -0.50% for the 360 ML-based nonlinear portfolios, and -0.30% for our 2.019 own-constructed nonlinear portfolios. Hence, the return premium for loading on war risk is, on average, 0.35% per month (or 4.2% per annum) across test assets.

The addition of the War Mimicking Portfolio (WMP) to the benchmark facatr models enhances their explanatory capacity by 9% to 14% while pricing 2,190 nonlinear portfolios and 360 machine learning-based nonlinear portfolios, respectively. Importantly, the mispricing error substantially decreases, from 3% to 0.61%. when we supplement WMP with other benchmarks to price the machine learning-based nonlinear portfolios. These results lead us to conclude that the WMP pricing of nonlinear portfolios aligns closely with the War Factor generated from a shock in the first-order autoregressive process.

7 Protocol of Factor Identification

In this section, we investigate the extent to which the War Mimicking Portfolio (WMP) qualifies as a priced risk factor in accordance with the criteria set forth by Pukthuanthong, Roll, and Subrahmanyam (2019). They assert that for a factor to be considered a genuine priced risk factor, it must satisfy three essential conditions. First, a necessary condition is that it be correlated with the systematic risk of returns or the covariance of returns. Second, a sufficient condition is that the factor must command a risk premium. Last, the factor must yield a reward-to-risk ratio that is reasonable in view of plausible levels of risk aversion and risk—an augmented condition. A detailed exposition of these criteria can be found in Appendix B. As reported in Table **??** and Table B2, WMP passes these three conditions, consistent with it being a priced risk factor.

8 *War* versus Other Media-Based Uncertainty Indexes

The previous section shows that *War* innovations command a negative risk premium across a wide range of test portfolios. However, the 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).[22] Thus, this section investigates whether our *War* contains information beyond these two measures by performing horserace analyses in the cross-sections.

We conduct the cross-sectional tests with the innovations in *War* (henceforth, *WarFac*), $NVIX^2$, and geopolitical risks (GPR). We construct these factors using Equation (8). As reported in Table 3, across all three sets of test assets, the economic and statistical magnitudes of $WarFac_t$ 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 significances vary across the test assets. When tested against $WarFac_t$, the GRP factor is significant only with the 360 ML-based nonlinear portfolios, while the $NVIX^2$ is completely subsumed across three sets of test assets. For the 360 ML-based nonlinear portfolios, GPR changes the sign to negative as it is highly correlated with *War* while *War* remains negative. The magnitude of its price of risk is about the same, suggesting the power of *War* encompasses that of GPR. [23]

Overall, we conclude that our *War* produces the empirical results most consistent with the predictions of the rare disaster models (Barro, 2006; Gabaix, 2012; Gourio, 2008) and it contains valuable information not captured by other empirical measures of rare disaster

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

[23] We also double-check by using the levels of these variables instead of their innovations. The results for *War* remain intact while GPR commands a negative risk premium, yet both GPR and $NVIX^2$ are again subsumed by *War* when tested together. We also try with our own constructed portfolios and obtain the same results, whether using levels or innovations of these variables. These results are not reported to conserve space but are available upon request.

risks.

9 *War* versus Crisis Events: Pricing Industry Returns

We next investigate whether the news-based *War* factor prices industry portfolios. Berkman, Jacobsen, and Lee (2011) measures empirical disaster risks by counting the number of crisis events each month.[24] They argue that the raw number of crisis events is a good proxy for investors' perception of rare disaster risks and show that factors constructed from crisis event counts price the Fama-French 30 industry portfolios with negative return premiums. We therefore test whether *War* has incremental predictive power beyond the real-world crisis factors.

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

$$R^e_{i\tau} = \alpha_{it} + \beta_{it} X_\tau + \beta^{MKT}_{it} MKT_\tau + \beta^{SMB}_{it} SMB_\tau + \beta^{HML}_{it} HML_\tau + \epsilon_{i\tau}, \tag{11}$$

where $R^e_{i\tau}$ is the excess return of portfolio i over month $t-59$ to month t, and X is either our *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 its previous month betas computed in the previous step:

$$R^e_{i\tau} = Intercept_t + \lambda_t \beta_{i,t-1} + \lambda^{MKT}_t \beta^{MKT}_{i,t-1} + \lambda^{SMB}_t \beta^{SMB}_{i,t-1} + \lambda^{HML}_t \beta^{HML}_{i,t-1} + e_{it}, \tag{12}$$

where the λ_t's 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's 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

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

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%. Our 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 along with the Fama-French three factors, both WarFac and CrisisFac have equal negative return premiums of 0.3%, significant the 5% level, while 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, while the return premium of CWarFac is not significant. In the last column, when all three crisis factors are included together with the three Fama-French factors, Warfac dominates the other two event-based crisis factors.

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

10 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 risk of rare disasters. We find that loadings on our war factor, *War*, 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, including long-short portfolios and machine-learning-based portfolios.

The return premium for loading on *War* is negative. In a rational asset pricing approach in which investors dislike rare disasters, this suggests that investors value the hedge provide by assets which 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 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 over-weight low probabilities as in the cumulative prospect theory value function. Such over-weighting of war risk implies undervaluation of stocks that are negatively sensitive to war risk and overvaluation of stocks that are positively sensitive. A long-short portfolio that buys undervalued stocks and sells overvalued stocks (i.e., a war factor) would therefore earn a positive return premium.

Moreover, our evidence suggests that *War* is not subsumed by NVIX and GPR, even when all factors 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 such risks. Our results further imply that the risk of war in particular is a crucial type of rare disaster for asset pricing.

References

Adrian, T., Etula, E., & Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *Journal of Finance*, *69*(6), 2557–2596.

Andersen, T. G., Fusari, N., & Todorov, V. (2015). The risk premia embedded in index options. *Journal of Financial Economics*, *117*(3), 558–584.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The journal of finance*, *61*(1), 259–299.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, *121*(3), 823–866.

Barro, R. J. (2009). Rare disasters, asset prices, and welfare costs. *American Economic Review*, *99*(1), 243–64.

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics*, *12*(1), 129–156.

Berkman, H., Jacobsen, B., & Lee, J. B. (2011). Time-varying rare disaster risk and stock returns. *Journal of Financial Economics*, *101*(2), 313–332.

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, *55*(4), 77–84.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, *3*(Jan), 993–1022.

Bollerslev, T., & Todorov, V. (2011). Tails, fears, and risk premia. *The Journal of Finance*, *66*(6), 2165–2211.

Bryzgalova, S., Pelger, M., & Zhu, J. (2020). Forest through the trees: Building cross-sections of stock returns. *Available at SSRN 3493458*.

Bybee, L., Kelly, B. T., Manela, A., & Xiu, D. (2021). *Business News and Business Cycles* (tech. rep.). National Bureau of Economic Research.

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, *112*(4), 1194–1225.

Chang, B. Y., Christoffersen, P., & Jacobs, K. (2013). Market skewness risk and the cross section of stock returns. *Journal of Financial Economics*, *107*(1), 46–68.

Christoffersen, P., Jacobs, K., & Ornthanalai, C. (2012). Dynamic jump intensities and risk premiums: Evidence from s&p500 returns and options. *Journal of Financial Economics*, *106*(3), 447–472.

Cochrane, J. H. (2005). *Asset pricing: Revised edition*. Princeton University Press.

Connor, G., & Korajczyk, R. A. (1988). Risk and return in an equilibrium apt: Application of a new test methodology. *Journal of Financial Economics*, *21*(2), 255–289.

Cooper, I., & Priestley, R. (2009). Time-varying risk premiums and the output gap. *Review of Financial Studies*, *22*(7), 2801–2833.

Cremers, M., Halling, M., & Weinbaum, D. (2015). Aggregate jump and volatility risk in the cross-section of stock returns. *The Journal of Finance*, *70*(2), 577–614.

Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short-and long-horizon behavioral factors. *Review of Financial Studies*, *33*(4), 1673–1736.

Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, *1*(2), 203–219.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *Journal of finance*, *40*(3), 793–805.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, *47*(2), 427–465.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, *128*(2), 234–252.

Freyberger, J., Neuhierl, A., & Weber, M. (2020). Dissecting characteristics nonparametrically. *Review of Financial Studies*, *33*(5), 2326–2377.

Gabaix, X. (2012). Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance. *Quarterly Journal of Economics*, *127*(2), 645–700.

Giglio, S., Xiu, D., & Zhang, D. (2021). *Test assets and weak factors* (tech. rep.). National Bureau of Economic Research.

Gourio, F. (2008). Disasters, recoveries, and predictability.

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National academy of Sciences*, *101*(suppl 1), 5228–5235.

He, Z., Kelly, B., & Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, *126*(1), 1–35.

Hirshleifer, D., Mai, D., & Pukthuanthong, K. (2023). War discourse and disaster premia: 160 years of evidence from stock and bond markets. *Working paper*.

Hou, K., Mo, H., Xue, C., & Zhang, L. (2021). An augmented q-factor model with expected growth. *Review of Finance*, *25*(1), 1–41.

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, *33*(5), 2019–2133.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of finance*, *45*(3), 881–898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of finance*, *48*(1), 65–91.

Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, *96*(2), 175–194.

Lu, B., Ott, M., Cardie, C., & Tsou, B. K. (2011). Multi-aspect sentiment analysis with topic models. *2011 IEEE 11th International Conference on Data Mining Workshops*, 81–88.

Manela, A., & Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics*, *123*(1), 137–162.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, 867–887.

Newey, W., & West, K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703–708.

Pontiff, J., & Woodgate, A. (2008). Share issuance and cross-sectional returns. *Journal of Finance*, *63*(2), 921–945.

Pukthuanthong, K., Roll, R., Junbo, W., & Tengfei, W. (2022). Testing Asset Pricing Model with Non-Traded Factors: A New Method to Resolve (Measurement/Econometric) Issues in Factor-Mimicking Portfolio. *SSRN*.

Pukthuanthong, K., Roll, R., & Subrahmanyam, A. (2019). A protocol for factor identification. *The Review of Financial Studies*, *32*(4), 1573–1607.

Rietz, T. A. (1988). The equity risk premium a solution. *Journal of Monetary Economics*, *22*(1), 117–131.

Santa-Clara, P., & Yan, S. (2010). Crashes, volatility, and the equity premium: Lessons from s&p 500 options. *The Review of Economics and Statistics*, *92*(2), 435–451.

Shanken, J. (1992). On the estimation of beta-pricing models. *Review of Financial Studies*, *5*(1), 1–33.

Shiller, R. J. (2019). *Narrative economics: How stories go viral and drive major economic events*. Princeton University Press.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review*, 289–315.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *Review of Financial Studies*, *30*(4), 1270–1315.

Steyvers, M., & Griffiths, T. (2007). Probabilistic topic models. In *Handbook of latent semantic analysis* (pp. 439–460). Psychology Press.

Wachter, J. A. (2013). Can time-varying risk of rare disasters explain aggregate stock market volatility? *Journal of Finance*, *68*(3), 987–1035.

Watanabe, K., & Zhou, Y. (2020). Theory-Driven Analysis of Large Corpora: Semisupervised Topic Classification of the UN Speeches. *Social Science Computer Review*.

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.

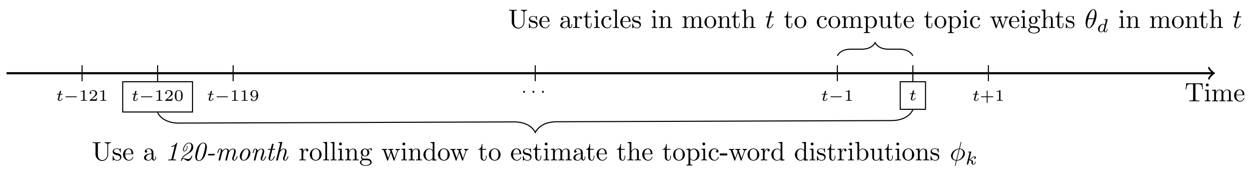

Figure 2. NYT Article Count and Length

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

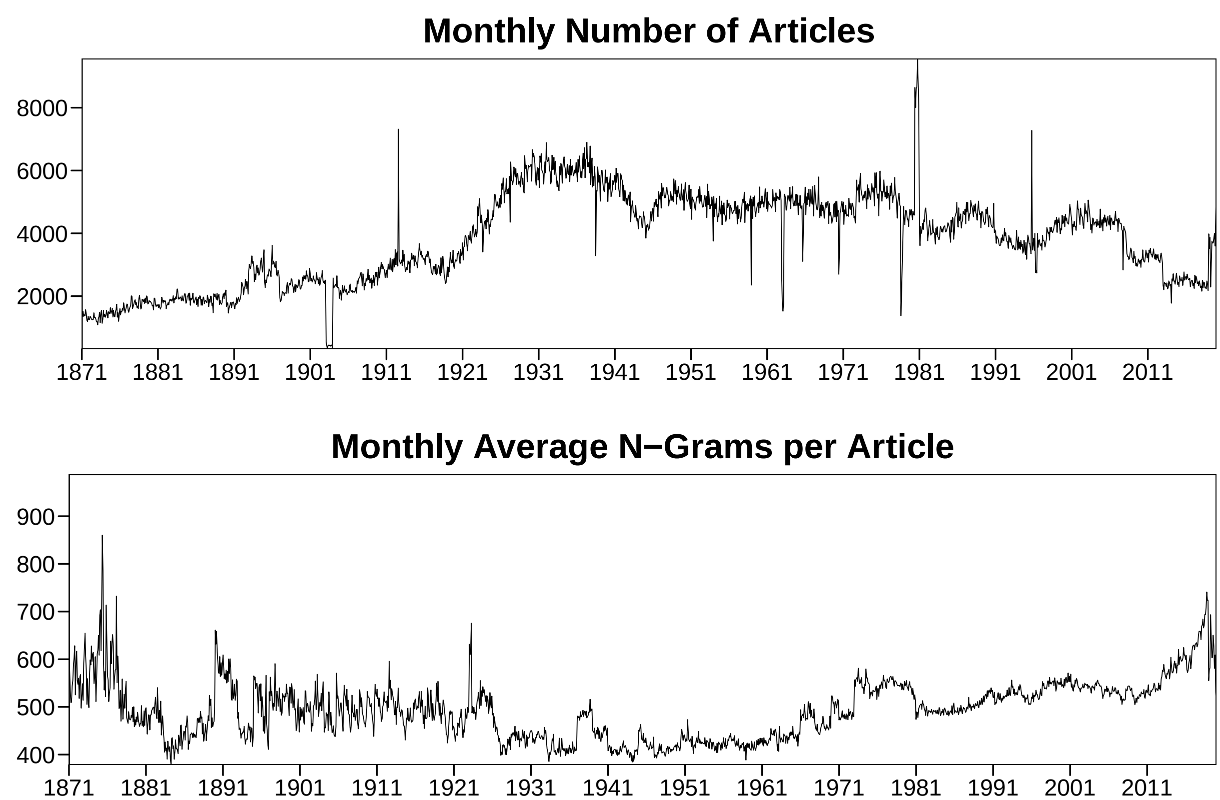

Figure 3. Narrative Contents

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 4. 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 solid line represents the topic weight, and the dashed line represents the excess market return; both have been demeaned to improve visualization. The gray-shaded areas represent NBER-defined recessions. The sample period is from January 1871 to October 2019.

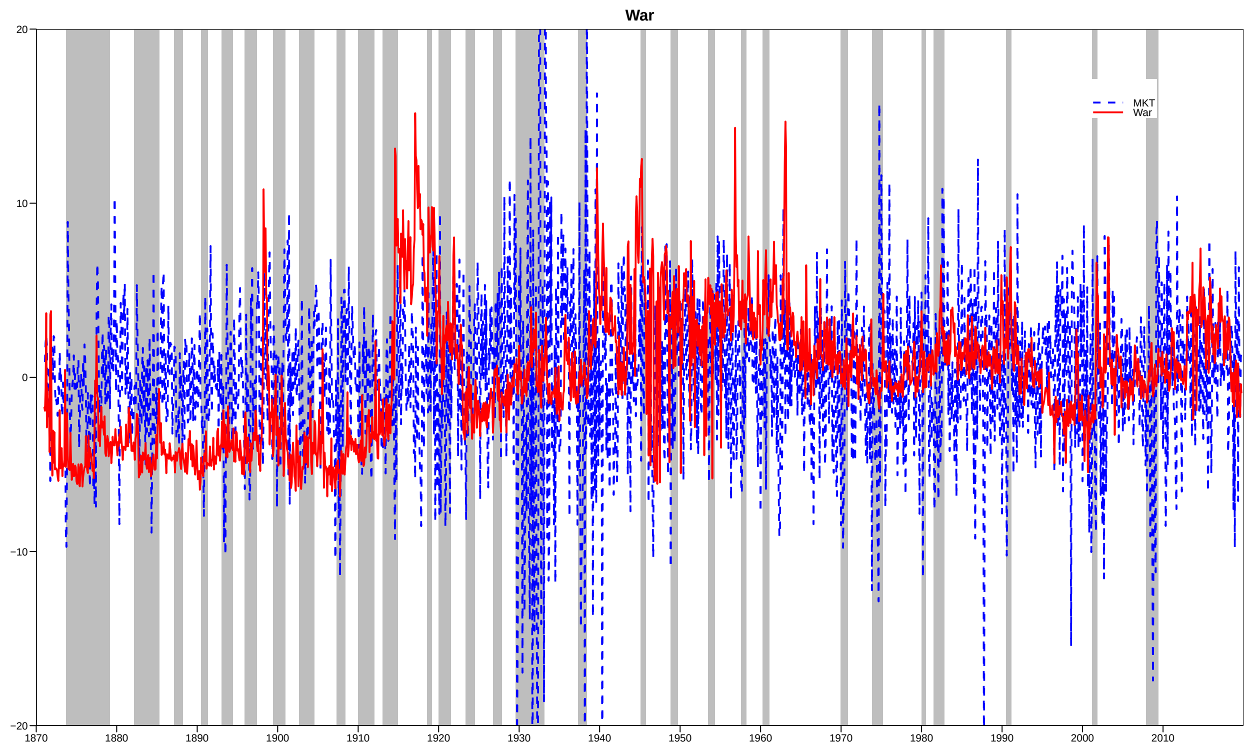

Figure 5. Articles Making the Biggest Contribution to *War* Spikes since 1990

This figure plots the ten articles that have contributed significantly to ten monthly heights of *War* since 1990. Topic weights are demeaned. The gray-shaded areas represent NBER-defined recessions. The sample period is from January 1990 to October 2019.

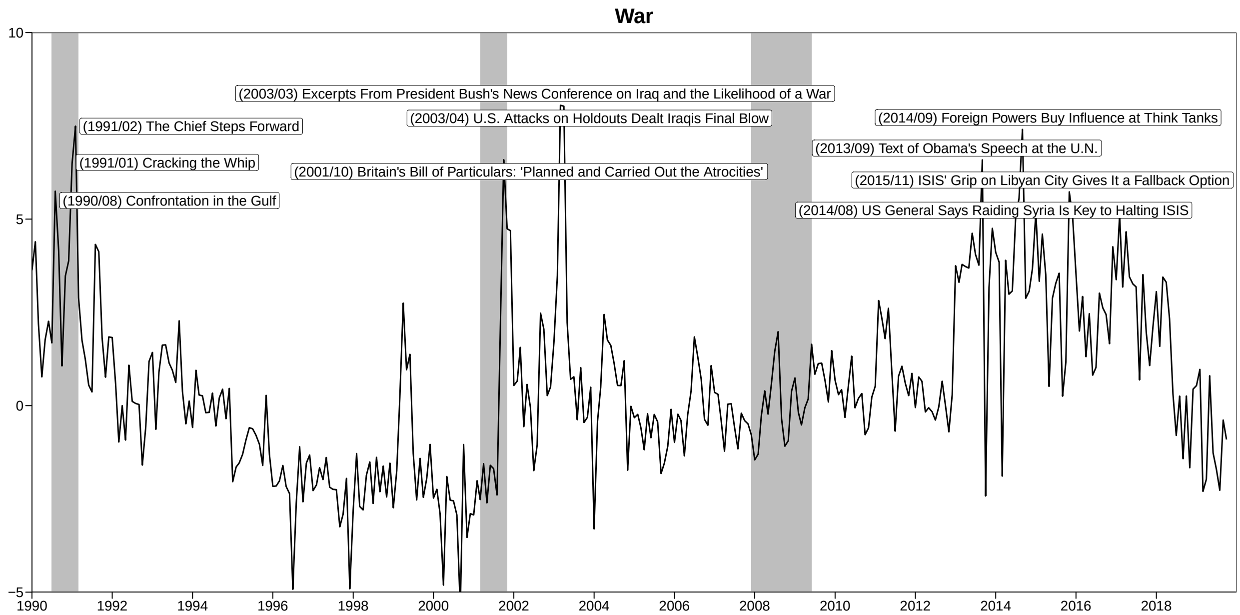

Table 1
***War* Factor and Risk Premium**

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas. Test assets include 118 long-minus-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, 1173 single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, and 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020) in Panel C. "WarFac" is the scaled innovations in NYT *War* ($WarFac_t$); "mkt, smb, hml, rmw, cma, mom" are Fama and French (2018)'s six factors; "mkt, smb, mgmt, perf" are Stambaugh and Yuan (2017)'s mispricing factors; "pead" and "fin" are Daniel, Hirshleifer, and Sun, 2020's behavioral factors; and "r_mkt, r_me, r_ia, r_roe, r_eg" are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. Reported are monthly risk premium and R^2 in percentages and t-statistic with Shanken (1992)'s correction. N is the number of test portfolios and T is the number of months. The sample is from July 1972 to December 2016.

Panel A: 118 Long-Minus-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.25 ***	0.16 ***	0.15 ***	0.09 ***	0.10 ***	0.15 ***	0.15 ***	0.12 ***	0.10 ***
	(4.14)	(7.08)	(4.81)	(3.23)	(3.00)	(4.80)	(3.80)	(3.08)	(2.83)
WarFac	-17.13 ***					-15.64 ***	-13.17 ***	-17.50 ***	-7.93 **
	(-2.67)					(-4.72)	(-4.46)	(-3.07)	(-2.57)
mkt		0.48	0.89 **	1.14 ***		0.44	0.74 *	1.07 **	
		(1.50)	(2.51)	(2.98)		(1.10)	(1.77)	(2.08)	
smb		0.05	-0.02			0.00	-0.05		
		(0.30)	(-0.15)			(0.00)	(-0.28)		
hml		0.27				0.28			
		(1.60)				(1.40)			
rmw		0.28 **				0.24 *			
		(2.27)				(1.66)			
cma		0.54 ***				0.50 ***			
		(4.91)				(3.90)			
mom		0.61 ***				0.77 ***			
		(2.91)				(3.41)			
mgmt			0.71 ***				0.57 ***		
			(4.50)				(3.20)		
perf			0.47 *				0.56 **		
			(1.93)				(2.03)		
pead				0.36 **				0.55 ***	
				(2.19)				(2.58)	
fin				0.96 ***				0.82 ***	
				(4.64)				(3.47)	
r_mkt					0.66 *				0.60
					(1.87)				(1.63)
r_me					0.25				0.28
					(1.48)				(1.62)
r_ia					0.44 ***				0.40 ***
					(3.66)				(3.24)
r_roe					0.33 **				0.35 **
					(2.40)				(2.46)
r_eg					0.80 ***				0.70 ***
					(6.05)				(4.66)
R^2	42	59	65	51	77	68	70	66	79
N	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532

Table 1
***War* Factor and Risk Premium (Cont.)**

Panel B: 1173 Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.71 ***	0.43 **	0.25	-0.22	0.35	0.42 *	0.21	-0.29	0.32
	(3.38)	(2.12)	(1.11)	(-0.81)	(1.55)	(1.90)	(0.88)	(-0.96)	(1.37)
WarFac	-8.08 **					-5.41 ***	-5.43 ***	-7.13 ***	-4.35 ***
	(-2.34)					(-4.56)	(-4.31)	(-3.73)	(-3.65)
mkt		0.16	0.34	0.84 **		0.18	0.38	0.92 **	
		(0.55)	(1.08)	(2.47)		(0.59)	(1.17)	(2.47)	
smb		0.16	0.20			0.13	0.15		
		(1.08)	(1.31)			(0.88)	(1.00)		
hml		0.30 **				0.31 **			
		(1.98)				(1.97)			
rmw		0.18				0.20 *			
		(1.56)				(1.67)			
cma		0.20 **				0.22 **			
		(2.06)				(2.21)			
mom		0.58 ***				0.62 ***			
		(2.84)				(3.05)			
mgmt			0.46 ***				0.44 ***		
			(2.89)				(2.71)		
perf			0.47 **				0.50 **		
			(2.12)				(2.23)		
pead				0.32 **				0.40 **	
				(2.13)				(2.53)	
fin				0.57 ***				0.60 ***	
				(2.84)				(2.90)	
r_mkt					0.24				0.27
					(0.77)				(0.87)
r_me					0.34 **				0.34 **
					(2.29)				(2.27)
r_ia					0.27 **				0.27 **
					(2.43)				(2.37)
r_roe					0.23 *				0.25 *
					(1.76)				(1.92)
r_eg					0.61 ***				0.58 ***
					(5.65)				(5.29)
R^2	16	42	43	34	55	46	47	41	57
N	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532

Table 1
***War* Factor and Risk Premium (Cont.)**

Panel C: 360 ML-based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.32	3.39 ***	3.28 ***	4.22 ***	2.11 ***	-0.25	0.47	-0.41	0.07
	(0.43)	(6.80)	(7.51)	(6.07)	(2.73)	(-0.23)	(0.55)	(-0.40)	(0.07)
WarFac	-33.29 ***					-55.48 ***	-44.59 ***	-46.74 ***	-44.22 ***
	(-2.67)					(-3.31)	(-3.47)	(-3.39)	(-3.39)
mkt		-3.39 ***	-3.24 ***	-3.86 ***		0.62	-0.08	0.77	
		(-6.06)	(-6.40)	(-5.47)		(0.55)	(-0.10)	(0.75)	
smb		0.18	0.12			-0.71 **	-0.87 ***		
		(1.04)	(0.64)			(-2.38)	(-3.21)		
hml		1.31 ***				0.83 *			
		(6.24)				(1.83)			
rmw		0.20				1.24 **			
		(0.95)				(2.53)			
cma		0.28 *				0.01			
		(1.81)				(0.03)			
mom		0.21				1.45 ***			
		(0.86)				(3.45)			
mgmt			1.32 ***				1.05 ***		
			(7.13)				(2.65)		
perf			0.03				0.86		
			(0.11)				(1.47)		
pead				-0.56 **				0.66	
				(-2.09)				(1.19)	
fin				0.83 **				2.17 ***	
				(2.54)				(3.81)	
r_mkt					-1.76 **				0.43
					(-2.17)				(0.45)
r_me					-0.15				-0.20
					(-0.66)				(-0.69)
r_ia					0.24				0.30
					(0.93)				(0.86)
r_roe					-0.17				0.91 **
					(-0.41)				(2.19)
r_eg					3.39 ***				1.88 **
					(5.95)				(2.55)
R^2	43	41	40	35	58	66	58	61	67
N	360	360	360	360	360	360	360	360	360
T	532	532	532	532	532	532	532	532	532

Table 2
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. Test assets include 118 long-minus-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, 1173 single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020) in Panel C, 104 own constructed anomalies in Panel D, and 1173 own constructed nonlinear portfolios in Panel E. "*WMP*" is the *War* mimicking portfolio; "mkt, smb, hml, rmw, cma, mom" are Fama and French (2018)'s six factors; "mkt, smb, mgmt, perf" are Stambaugh and Yuan (2017)'s mispricing factors; "pead" and "fin" are Daniel, Hirshleifer, and Sun, 2020's behavioral factors; and "r_mkt, r_me, r_ia, r_roe, r_eg" are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. Reported are monthly risk premium and R^2 in percentages and t-statistic with Shanken (1992)'s correction. N is the number of test portfolios and T is the number of months. The sample is from July 1972 to December 2016.

Panel A: 118 Long-Minus-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.19 ***	0.16 ***	0.15 ***	0.09 ***	0.10 ***	0.18 ***	0.14 ***	0.09 ***	0.09 ***
	(4.95)	(7.08)	(4.81)	(3.23)	(3.00)	(8.35)	(5.27)	(3.31)	(3.19)
WMP	-0.51 ***					-0.77 ***	-0.60 ***	-0.79 ***	-0.51 ***
	(-3.49)					(-3.71)	(-3.44)	(-3.80)	(-2.60)
mkt		0.48	0.89 **	1.14 ***		0.51	0.91 **	1.22 ***	
		(1.50)	(2.51)	(2.98)		(1.56)	(2.57)	(3.13)	
smb		0.05	-0.02			0.10	-0.02		
		(0.30)	(-0.15)			(0.58)	(-0.11)		
hml		0.27				0.26			
		(1.60)				(1.50)			
rmw		0.28 **				0.22 *			
		(2.27)				(1.79)			
cma		0.54 ***				0.56 ***			
		(4.91)				(5.04)			
mom		0.61 ***				0.55 ***			
		(2.91)				(2.64)			
mgmt			0.71 ***				0.66 ***		
			(4.50)				(4.32)		
perf			0.47 *				0.45 *		
			(1.93)				(1.85)		
pead				0.36 **				0.32 **	
				(2.19)				(2.02)	
fin				0.96 ***				0.89 ***	
				(4.64)				(4.08)	
r_mkt					0.66 *				0.71 *
					(1.87)				(1.91)
r_me					0.25				0.25
					(1.48)				(1.41)
r_ia					0.44 ***				0.41 ***
					(3.66)				(3.73)
r_roe					0.33 **				0.32 **
					(2.40)				(2.28)
r_eg					0.80 ***				0.79 ***
					(6.05)				(5.98)
R^2	38	59	65	51	77	61	65	51	77
N	138	138	138	138	138	138	138	138	138
T	532	532	532	532	532	532	532	532	532

Table 2
War Mimicking Portfolio and Risk Premium (Cont.)

Panel B: 1173 Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.66 ***	0.43 **	0.25	-0.22	0.35	0.43 **	0.27	-0.22	0.26
	(3.57)	(2.12)	(1.11)	(-0.81)	(1.55)	(2.06)	(1.19)	(-0.84)	(1.10)
WMP	-0.28 *					-0.34 **	-0.41 ***	-0.43 ***	-0.41 ***
	(-1.87)					(-2.49)	(-2.59)	(-2.95)	(-2.64)
mkt		0.16	0.34	0.84 **		0.17	0.32	0.85 **	
		(0.55)	(1.08)	(2.47)		(0.58)	(1.02)	(2.50)	
smb		0.16	0.20			0.16	0.21		
		(1.08)	(1.31)			(1.14)	(1.36)		
hml		0.30 **				0.31 **			
		(1.98)				(2.01)			
rmw		0.18				0.18			
		(1.56)				(1.50)			
cma		0.20 **				0.20 **			
		(2.06)				(2.10)			
mom		0.58 ***				0.57 ***			
		(2.84)				(2.81)			
mgmt			0.46 ***				0.36 **		
			(2.89)				(2.51)		
perf			0.47 **				0.43 *		
			(2.12)				(1.91)		
pead				0.32 **				0.32 **	
				(2.13)				(2.20)	
fin				0.57 ***				0.56 ***	
				(2.84)				(2.75)	
r_mkt					0.24				0.33
					(0.77)				(1.05)
r_me					0.34 **				0.31 **
					(2.29)				(2.11)
r_ia					0.27 **				0.20 *
					(2.43)				(1.91)
r_roe					0.23 *				0.20
					(1.76)				(1.48)
r_eg					0.61 ***				0.60 ***
					(5.65)				(5.48)
R^2	19	42	43	34	55	42	45	34	57
N	1372	1372	1372	1372	1372	1372	1372	1372	1372
T	532	532	532	532	532	532	532	532	532

Table 2
War Mimicking Portfolio and Risk Premium (Cont.)

Panel C: 360 ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.84 ***	3.39 ***	3.28 ***	4.22 ***	2.11 ***	0.16	0.76	2.92 ***	0.78
	(4.26)	(6.80)	(7.51)	(6.07)	(2.73)	(0.26)	(1.28)	(4.29)	(0.99)
WMP	-0.65 ***					-2.94 ***	-2.19 ***	-1.29 ***	-1.73 ***
	(-3.27)					(-6.97)	(-6.95)	(-5.23)	(-4.03)
mkt		-3.39 ***	-3.24 ***	-3.86 ***		0.22	-0.69	-2.47 ***	
		(-6.06)	(-6.40)	(-5.47)		(0.35)	(-1.06)	(-3.66)	
smb		0.18	0.12			-0.01	0.08		
		(1.04)	(0.64)			(-0.04)	(0.35)		
hml		1.31 ***				-0.03			
		(6.24)				(-0.11)			
rmw		0.20				0.57 *			
		(0.95)				(1.89)			
cma		0.28 *				-0.23			
		(1.81)				(-0.92)			
mom		0.21				0.94 ***			
		(0.86)				(3.43)			
mgmt			1.32 ***				-0.74 **		
			(7.13)				(-2.45)		
perf			0.03				0.30		
			(0.11)				(0.78)		
pead				-0.56 **				-0.61 *	
				(-2.09)				(-1.84)	
fin				0.83 **				-0.14	
				(2.54)				(-0.28)	
r_mkt					-1.76 **				-0.41
					(-2.17)				(-0.49)
r_me					-0.15				-0.18
					(-0.66)				(-0.74)
r_ia					0.24				-0.94 ***
					(0.93)				(-2.62)
r_roe					-0.17				0.05
					(-0.41)				(0.13)
r_eg					3.39 ***				2.71 ***
					(5.95)				(4.56)
R^2	13	41	40	35	58	63	57	42	70
N	360	360	360	360	360	360	360	360	360
T	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. Test assets include 118 long-minus-short portfolio from Hou, Xue, and Zhang (2020) in Panel A, 1173 single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, and 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020) in Panel C. *WarFac* is the scaled innovations in NYT *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). Monthly risk premium and R^2 in percentages and t-statistic with Shanken (1992)'s correction. N is the number of test portfolios, and T is the number of months. The sample is from January 1967 to March 2016.

Panel A: 118 Long-Minus-Short Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)
Intercept	0.25 ***	0.19 ***	0.17 ***	0.18 ***
	(4.69)	(5.21)	(5.52)	(3.86)
WarFac	-15.03 ***			-12.25 **
	(-2.88)			(-1.99)
NVIX2Fac		11.53 **		1.70
		(2.57)		(0.25)
GPRFac			13.45 *	9.88
			(1.67)	(1.01)
R^2	36	17	4	54
N	118	118	118	118
T	588	588	588	588

Panel B: 1173 Single-Sorted Portfolios from Hou, Xue, and Zhang (2020)

	(1)	(2)	(3)	(4)
Intercept	0.66 ***	0.84 ***	0.65 ***	0.80 ***
	(3.40)	(4.76)	(3.62)	(3.95)
WarFac	-6.85 **			-6.52 **
	(-2.17)			(-2.42)
NVIX2Fac		4.59		0.22
		(1.15)		(0.05)
GPRFac			4.73	2.13
			(1.33)	(0.61)
R^2	12	6	1	19
N	1173	1173	1173	1173
T	588	588	588	588

Table 3
Cross-Sectional Tests: *War* versus NVIX^2 and GPR (Cont.)

Panel C: 360 ML-Based Portfolios from Bryzgalova, Pelger, and Zhu (2020)

	(1)	(2)	(3)	(4)
Intercept	0.41	2.31 ***	0.59 ***	1.54 *
	(0.47)	(7.92)	(2.84)	(1.82)
WarFac	-40.51 ***			-40.89 ***
	(-2.98)			(-2.67)
NVIX2Fac		27.14 ***		20.24
		(3.77)		(0.91)
GPRFac			17.37	-62.11 **
			(1.08)	(-2.08)
R^2	51	21	0	59
N	360	360	360	360
T	588	588	588	588

Table 4
Cross-Sectional Tests: *War* versus Crisis Events

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

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

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

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
Spanning Test

	(1)	(2)	(3)	(4)	(5)
Alpha	-0.241 ***	-0.186 **	-0.295 ***	-0.242 ***	-0.258 ***
	(-3.354)	(-2.387)	(-3.786)	(-3.012)	(-3.514)
MKT	-0.053 **	-0.057 **	-0.025		-0.108
	(-2.476)	(-2.242)	(-1.142)		(-0.044)
SMB	-0.024	-0.090 *			-0.059
	(-0.723)	(-1.887)			(-0.610)
HML	0.071 *				-0.079
	(1.654)				(-1.310)
RMW	0.260 ***				0.195 ***
	(5.771)				(2.663)
CMA	0.013				0.069
	(0.177)				(0.494)
MOM	0.017				0.056
	(0.529)				(1.404)
MGMT		0.101 **			-0.033
		(2.496)			(-0.414)
PERF		0.015			-0.173 ***
		(0.465)			(-3.126)
PEAD			-0.001		0.031
			(-0.012)		(0.504)
FIN			0.190 ***		0.169 ***
			(6.101)		(2.867)
R_MKT				-0.066 ***	0.049
				(-2.828)	(0.020)
R_ME				-0.036	0.085
				(-0.858)	(0.850)
R_IA				0.149 ***	-0.075
				(2.644)	(-0.617)
R_ROE				0.208 ***	0.146 *
				(4.134)	(1.957)
R_EG				-0.050	-0.046
				(-0.884)	(-0.740)
R^2	0.208	0.121	0.196	0.170	0.269

Internet Appendix
War Discourse and the Cross-Section of Returns

A Additional Results with Our Own Test Portfolios

This subsection presents the additional results with our own constructed portfolios in Table A1 and Table A3. We discuss the pricing implications in the main text.

Table A1
War Factor and Risk Premium

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas. Test assets include 104 own constructed anomalies in Panel A and 1173 own constructed nonlinear portfolios in Panel B. "*WarFac*" is the scaled innovations in NYT *War*; "mkt, smb, hml, rmw, cma, mom" are Fama and French (2018)'s six factors; "mkt, smb, mgmt, perf" are Stambaugh and Yuan (2017)'s mispricing factors; "pead" and "fin" are Daniel, Hirshleifer, and Sun (2020)'s behavioral factors; and "r_mkt, r_me, r_ia, r_roe, r_eg" are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. Reported are monthly risk premium and R^2 in percentages and t-statistic with Shanken (1992)'s correction. N is the number of test portfolios and T is the number of months. The sample is from July 1972 to December 2016.

Panel A: 104 Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.29 ***	-0.37 ***	-0.35 ***	-0.41 ***	-0.36 ***	-0.37 ***	-0.33 ***	-0.32 ***	-0.35 ***
	(-5.25)	(-16.54)	(-13.05)	(-12.78)	(-10.62)	(-8.48)	(-7.03)	(-6.11)	(-8.33)
WarFac	-20.17 ***					-24.67 ***	-20.68 ***	-22.83 ***	-16.85 ***
	(-3.00)					(-4.91)	(-4.53)	(-3.73)	(-4.24)
mkt		0.09	0.41	0.82 **		-0.13	-0.04	0.26	
		(0.33)	(1.48)	(2.51)		(-0.32)	(-0.10)	(0.57)	
smb		0.24	0.34 **			0.18	0.16		
		(1.57)	(2.00)			(0.89)	(0.78)		
hml		0.33 **				0.44 **			
		(2.16)				(2.14)			
rmw		0.09				0.21			
		(0.74)				(1.30)			
cma		0.26 ***				0.26 *			
		(2.62)				(1.87)			
mom		0.74 ***				0.86 ***			
		(3.50)				(3.20)			
mgmt			0.50 ***				0.43 **		
			(3.26)				(2.18)		
perf			0.63 ***				0.67 **		
			(2.86)				(2.29)		
pead				0.47 ***				0.55 **	
				(2.91)				(2.08)	
fin				0.42 **				0.54 **	
				(2.08)				(2.09)	
r_mkt					0.50				0.17
					(1.59)				(0.47)
r_me					0.51 ***				0.56 **
					(2.59)				(2.46)
r_ia					0.33 ***				0.29 **
					(2.70)				(2.10)
r_roe					0.15				0.23
					(0.97)				(1.40)
r_eg					1.26 ***				0.90 ***
					(7.43)				(4.80)
R^2	30	23	30	14	47	44	45	39	54
N	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532

Table A1
War Factor and Risk Premium (Cont.)

Panel B: 2190 Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.97 ***	0.96 ***	1.03 ***	1.37 ***	1.02 ***	0.76 ***	0.88 ***	0.74 ***	0.83 ***
	(3.17)	(4.72)	(5.07)	(5.28)	(4.71)	(3.23)	(3.64)	(2.61)	(3.17)
WarFac	-9.72 ***					-11.01 ***	-10.55 ***	-13.85 ***	-11.72 ***
	(-2.99)					(-5.98)	(-4.74)	(-4.40)	(-6.33)
mkt		-0.29	-0.32	-0.29		0.00	-0.01	0.31	
		(-0.96)	(-1.04)	(-0.94)		(0.01)	(-0.02)	(0.90)	
smb		0.32 *	0.32			0.10	-0.01		
		(1.84)	(1.61)			(0.55)	(-0.04)		
hml		0.15				0.15			
		(0.91)				(0.85)			
rmw		0.23				0.42 **			
		(1.46)				(2.52)			
cma		0.57 ***				0.50 ***			
		(4.98)				(3.97)			
mom		0.53 **				0.76 ***			
		(2.33)				(3.29)			
mgmt			0.48 ***				0.51 ***		
			(2.90)				(2.78)		
perf			0.58 **				0.80 ***		
			(2.36)				(2.93)		
pead				0.29 *				0.56 **	
				(1.70)				(2.51)	
fin				0.38				0.82 ***	
				(1.52)				(3.01)	
r_mkt					-0.26				0.04
					(-0.87)				(0.11)
r_me					0.29 *				0.17
					(1.72)				(0.92)
r_ia					0.33 **				0.32 **
					(2.51)				(2.08)
r_roe					0.24				0.51 **
					(1.27)				(2.53)
r_eg					0.88 ***				0.92 ***
					(4.48)				(3.83)
R^2	13	48	46	30	48	55	54	49	56
N	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532

Table A2
War Factor versus Individual Risk Factors

This table presents the results from the second-pass cross-sectional regressions of average portfolio returns on factor betas. Test assets include 118 long-minus-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, 1173 single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, and 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020) in Panel C, 104 own constructed anomalies in Panel D, and 1173 own constructed nonlinear portfolios in Panel E. "*WarFac*" is the scaled innovations in NYT *War*; MKT, SMB, HML, RMW, CMA, MOM are Fama and French (2018)'s six factors; MGMT and PERF are Stambaugh and Yuan (2017)'s mispricing factors; PEAD and FIN are Daniel, Hirshleifer, and Sun (2020)'s behavioral factors; and R_IA, R_ROE, R_EG are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. Reported are monthly risk premium and R^2 in percentages and t-statistic with Shanken (1992)'s correction. N is the number of test portfolios and T is the number of months. The sample is from July 1972 to December 2016.

	WarFac	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Panel A: 118 Long-Minus-Short Portfolios														
Intercept	0.24 ***	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)	(5.61)	(6.08)	(6.58)	(6.33)	(4.98)	(6.64)	(5.95)	(6.04)	(6.57)	(5.27)	(6.34)	(5.81)	(4.70)
Factor	-17.25 ***	-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)	(-2.77)	(-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	24	4	21	9	13	35	37	7	4	34	39	8	30
N	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
Panel B: 1173 Single-Sorted Portfolios														
	WarFac	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	0.72 ***	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)	(4.29)	(3.95)	(4.07)	(3.66)	(4.07)	(4.71)	(5.16)	(3.96)	(3.46)	(4.98)	(4.74)	(3.86)	(5.22)
Factor	-8.42 **	-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)	(-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	10	2	15	8	11	18	16	8	4	16	19	8	17
N	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
Panel C: 360 ML-Based Portfolios														
	WarFac	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	0.43	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)	(10.24)	(2.71)	(3.97)	(2.80)	(4.21)	(6.11)	(8.23)	(4.01)	(2.46)	(7.39)	(7.24)	(3.01)	(6.42)
Factor	-36.37 ***	-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)	(-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	24	0	22	2	3	28	15	3	0	13	21	1	9
N	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
Panel D: 104 Own Constructed Anomalies														
	WarFac	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	-0.29 ***	-0.39 ***	-0.41 ***	-0.35 ***	-0.43 ***	-0.41 ***	-0.32 ***	-0.35 ***	-0.42 ***	-0.44 ***	-0.38 ***	-0.33 ***	-0.41 ***	-0.40 ***
	(-5.18)	(-10.56)	(-10.80)	(-12.60)	(-11.14)	(-10.60)	(-10.27)	(-9.89)	(-10.08)	(-12.26)	(-10.66)	(-9.64)	(-9.98)	(-10.51)
Factor	-19.99 ***	-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)	(-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	3	-1	7	6	0	11	7	2	5	4	10	0	4
N	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
Panel E: 2190 Own Constructed Nonlinear Portfolios														
	WarFac	MKT	SMB	HML	MOM	RMW	CMA	MGMT	PERF	PEAD	FIN	R_IA	R_ROE	R_EG
Intercept	0.99 ***	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)	(6.00)	(6.37)	(5.17)	(6.47)	(6.23)	(6.63)	(7.09)	(7.18)	(5.40)	(6.88)	(6.65)	(6.44)	(7.03)
Factor	-11.13 ***	-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)	(-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	27	13	29	19	20	36	30	25	7	27	33	18	28
N	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

Table A3
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. Test assets include 104 own constructed anomalies in Panel A and 1173 own constructed nonlinear portfolios in Panel B. "*WMP*" is the *War* mimicking portfolio; "mkt, smb, hml, rmw, cma, mom" are Fama and French (2018)'s six factors; "mkt, smb, mgmt, perf" are Stambaugh and Yuan (2017)'s mispricing factors; "pead" and "fin" are Daniel, Hirshleifer, and Sun (2020)'s behavioral factors; and "r_mkt, r_me, r_ia, r_roe, r_eg" are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. Reported are monthly risk premium and R^2 in percentages and t-statistic with Shanken (1992)'s correction. N is the number of test portfolios and T is the number of months. The sample is from July 1972 to December 2016.

Panel A: 104 Own Constructed Anomalies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.37 ***	-0.37 ***	-0.35 ***	-0.41 ***	-0.36 ***	-0.36 ***	-0.36 ***	-0.41 ***	-0.38 ***
	(-10.65)	(-16.54)	(-13.05)	(-12.78)	(-10.62)	(-14.09)	(-14.66)	(-12.86)	(-12.62)
WMP	-0.20					-1.04 ***	-0.34 **	-0.53 ***	-0.48 **
	(-1.35)					(-6.07)	(-2.09)	(-3.57)	(-2.30)
mkt		0.09	0.41	0.82 **		0.45	0.45	0.89 ***	
		(0.33)	(1.48)	(2.51)		(1.56)	(1.63)	(2.72)	
smb		0.24	0.34 **			0.26 *	0.35 **		
		(1.57)	(2.00)			(1.66)	(2.09)		
hml		0.33 **				0.32 **			
		(2.16)				(2.00)			
rmw		0.09				0.04			
		(0.74)				(0.29)			
cma		0.26 ***				0.25 **			
		(2.62)				(2.38)			
mom		0.74 ***				0.86 ***			
		(3.50)				(3.94)			
mgmt			0.50 ***				0.45 ***		
			(3.26)				(3.11)		
perf			0.63 ***				0.62 ***		
			(2.86)				(2.78)		
pead				0.47 ***				0.42 ***	
				(2.91)				(2.60)	
fin				0.42 **				0.31	
				(2.08)				(1.46)	
r_mkt					0.50				0.68 **
					(1.59)				(2.10)
r_me					0.51 ***				0.51 ***
					(2.59)				(2.60)
r_ia					0.33 ***				0.23 **
					(2.70)				(2.09)
r_roe					0.15				0.13
					(0.97)				(0.84)
r_eg					1.26 ***				1.22 ***
					(7.43)				(6.66)
R^2	6	23	30	14	47	27	30	14	47
N	128	128	128	128	128	128	128	128	128
T	532	532	532	532	532	532	532	532	532

Table A3
War Mimicking Portfolio and Risk Premium (Cont.)

Panel B: 2190 Own Constructed Nonlinear Portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	1.11 ***	0.96 ***	1.03 ***	1.37 ***	1.02 ***	0.27	0.39 **	0.88 ***	0.48 **
	(5.52)	(4.72)	(5.07)	(5.28)	(4.71)	(1.29)	(2.19)	(3.58)	(2.42)
WMP	-0.35 **					-1.29 ***	-0.87 ***	-0.94 ***	-0.78 ***
	(-1.96)					(-7.37)	(-4.88)	(-6.12)	(-4.11)
mkt		-0.29	-0.32	-0.29		0.51 *	0.19	0.33	
		(-0.96)	(-1.04)	(-0.94)		(1.71)	(0.64)	(1.13)	
smb		0.32 *	0.32			0.27	0.38 *		
		(1.84)	(1.61)			(1.40)	(1.77)		
hml		0.15				-0.06			
		(0.91)				(-0.29)			
rmw		0.23				0.33 *			
		(1.46)				(1.94)			
cma		0.57 ***				0.49 ***			
		(4.98)				(3.85)			
mom		0.53 **				0.71 ***			
		(2.33)				(3.02)			
mgmt			0.48 ***				0.17		
			(2.90)				(0.92)		
perf			0.58 **				0.44 *		
			(2.36)				(1.66)		
pead				0.29 *				0.19	
				(1.70)				(0.98)	
fin				0.38				0.14	
				(1.52)				(0.46)	
r_mkt					-0.26				0.25
					(-0.87)				(0.84)
r_me					0.29 *				0.26
					(1.72)				(1.51)
r_ia					0.33 **				0.09
					(2.51)				(0.68)
r_roe					0.24				0.15
					(1.27)				(0.75)
r_eg					0.88 ***				0.79 ***
					(4.48)				(3.68)
R^2	30	48	46	30	48	60	54	38	53
N	2190	2190	2190	2190	2190	2190	2190	2190	2190
T	532	532	532	532	532	532	532	532	532

B Protocol for Factor Identification

B.1 First criterion: Correlation of FMPs with the Systematic Risk of Returns

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

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

Finally, from the second step above, we compute the canonical correlation between the factor candidates and the corresponding eigenvectors. First, we use the L eigenvectors from step 2 and the K factor candidates from step 3 and calculate the covariance matrix over a sample period t, V_t $(L + K \times L + K)$. We break out a submatrix from the covariance matrix V_t in each period, the cross-covariance matrix, denoted by C_t having K rows and L columns. The entry in the i^{th} row and j^{th} column is the covariance between factor candidate i and eigenvector j. We need to break out the covariance submatrix of the factor candidates, $V_{f,t}$ $(K \times K)$, and the covariance submatrix of the real eigenvectors, $V_{e,t}$ $(L \times L)$. We then can find two weighting column vectors, λ_t and κ_t on the factor candidates and eigenvectors, respectively (λ_t has K rows, κ_t has L rows), that maximizes the correlation between the two weighted vectors. The covariance between the weighted averages of factor candidates and eigenvectors is $\lambda_t' C_t \kappa_t$, and their correlation is

$$\rho = \frac{\lambda_t' C_t \kappa_t}{\sqrt{\lambda_t' V_{f,t} \lambda_t \kappa_t' V_{e,t} \kappa_t}} \tag{13}$$

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

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

We compute asymptotic PCs that represent the covariance matrix. We split the overall sample into five subsamples with ten years.[1] For each subsample, we use CK to extract PCs and retain the first ten PCs, which account for close to 90% of the cumulative eigenvalues

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

or the total volatility in the covariance matrix, implying they capture most of the stock variations.

Next, we proceed to estimate the canonical correlations. We have several factor candidates and, thus, several pairs of canonical variates. We take the following steps to derive the significance levels of each factor candidate reported in the first row of Table ??. First, for each of the ten canonical pairs, the eigenvector weights for the ten CK PCs are taken, and the weighted average CK PC or the canonical variate for the ten CK PCs that produced the canonical correlation for this particular pair is constructed.[2] Then a regression using each CK PC canonical variate as the dependent variable and the actual candidate factor values as independent variables are run over the sample months in each subperiod. The square root of the R-squared from the regression is the canonical correlation. After proper normalization, the coefficients for the regressions are equal to the eigenvector's weighting elements for the candidate factors. The t-statistic from the regression then gives the significance level of each candidate factor. With the ten pairs of canonical variates in each subperiod, and a canonical correlation for each one, we have 50 such regressions. The first row presents the mean t-statistic of all canonical correlations. The second row shows the mean t-statistic across cases when the canonical correlation is statistically significant. The last row shows the average number of significant canonical correlations across subperiods.

A risk factor *must* satisfy the necessary and sufficient conditions: (1) the FMP is significantly related to any canonical variate in all decades, or it has a mean t-statistic exceeding the one-tailed 2.5% cutoff based on the Chi-squared value, and (2), in each sub-period, the risk factor has an average number of significant canonical correlations exceeding 2.50 (the bottom row of each panel). Researchers should test the augmented condition (the third condition) to ensure the robustness of the result. We leave it for other researchers to implement it. [3] We examine this criterion for the WMP.

Notably, as reported in Table ??, WMP passes this criterion in all test assets, with a

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

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

consistent average t-stat of the significant CC of 2 and the number of the significant CC of 3.5, well above 2.5. Only WMP, MKT, HML, and MOM pass this criterion in all testing assets. MKT represents the most substantial pass. We conclude that risk factors are WMP, MKT, HML, and MOM.

B.2 Second criterion: Risk premium estimation using FMPs

The second criterion of the PRS protocol requires that the global risk factors or the factors that pass the necessary condition command a risk premium in the cross-section of asset returns. To perform this step, we re-run the standard two-pass test with the factors that pass the necessary condition. We report in Table B2 that except for the 1173 single-sorted portfolios, WMP prices the other four sets of test assets after controlling all the other risk factors that pass the first criterion of the protocol. We conclude that our *War* factor is a genuine risk factor.

Table B1
Protocol Step 1: Correlation of WMP with the Systematic Risk of Returns

This table presents the results from the first step (necessary condition) of the protocol in Pukthuanthong, Roll, and Subrahmanyam, 2019. Test assets include 118 long-minus-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, 1173 single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020) in Panel C, 104 own constructed anomalies in Panel D, and 1173 own constructed nonlinear portfolios in Panel E. "*WMP*" is the *War* mimicking portfolio; "mkt, smb, hml, rmw, cma, mom" are Fama and French (2018)'s six factors; "mkt, smb, mgmt, perf" are Stambaugh and Yuan (2017)'s mispricing factors; and "r_mkt, r_me, r_ia, r_roe, r_eg" are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. The sample is from January 1967 to December 2016.

Panel A: 118 LMS Anomalies

	mkt	smb	hml	mom	rmw	cma	WMP	mgmt	perf	r_me	r_ia	r_roe	r_eg
Avg. T	1.67	1.36	2.23	3.25	2.26	1.44	1.64	1.66	1.56	1.36	1.34	2.01	2.14
Avg t (Sig. CC)	1.83	1.49	2.62	3.95	2.62	1.54	1.86	1.83	1.76	1.48	1.42	2.30	2.52
Decade 1	3.00	4.00	4.00	6.00	4.00	3.00	4.00	3.00	3.00	1.00	0.00	4.00	3.00
Decade 2	3.00	4.00	6.00	5.00	5.00	4.00	5.00	0.00	3.00	6.00	4.00	4.00	4.00
Decade 3	4.00	2.00	4.00	3.00	6.00	2.00	3.00	3.00	2.00	1.00	1.00	3.00	6.00
Decade 4	4.00	1.00	4.00	4.00	3.00	2.00	4.00	3.00	3.00	2.00	3.00	7.00	3.00
Decade 5	2.00	2.00	4.00	4.00	4.00	2.00	4.00	5.00	2.00	2.00	3.00	3.00	4.00
# Sign. CC	3.20	2.60	4.40	4.40	4.40	2.60	4.00	2.80	2.60	2.40	2.20	4.20	4.00

Panel B: 1173 Single Sorted Portfolios

	mkt	smb	hml	mom	rmw	cma	WMP	mgmt	perf	r_me	r_ia	r_roe	r_eg
Avg. T	17.06	1.50	2.71	3.80	2.16	1.73	1.99	1.94	2.33	1.40	1.35	2.07	2.14
Avg t (Sig. CC)	20.19	1.63	3.07	4.43	2.42	1.90	2.17	2.15	2.58	1.49	1.38	2.32	2.41
Decade 1	5.00	5.00	4.00	8.00	4.00	3.00	5.00	3.00	6.00	2.00	1.00	2.00	5.00
Decade 2	6.00	6.00	5.00	5.00	3.00	6.00	6.00	3.00	5.00	4.00	3.00	4.00	5.00
Decade 3	4.00	1.00	3.00	3.00	6.00	2.00	3.00	5.00	2.00	0.00	1.00	5.00	2.00
Decade 4	5.00	2.00	7.00	5.00	5.00	4.00	3.00	6.00	4.00	4.00	5.00	3.00	5.00
Decade 5	4.00	0.00	5.00	3.00	4.00	3.00	3.00	4.00	4.00	2.00	2.00	6.00	3.00
# Sign. CC	4.80	2.80	4.80	4.80	4.40	3.60	4.00	4.20	4.20	2.40	2.40	4.00	4.00

Panel C: 360 ML-Based Nonlinear Portfolios

	mkt	smb	hml	mom	rmw	cma	WMP	mgmt	perf	r_me	r_ia	r_roe	r_eg
Avg. T	11.23	1.80	1.86	2.90	1.35	1.24	1.65	1.26	1.34	1.43	1.12	1.62	1.14
Avg t (Sig. CC)	17.15	2.43	2.51	4.09	1.62	1.37	2.15	1.53	1.60	1.85	1.21	2.10	1.35
Decade 1	4.00	3.00	5.00	3.00	2.00	4.00	5.00	1.00	2.00	2.00	2.00	4.00	1.00
Decade 2	3.00	3.00	4.00	3.00	1.00	3.00	3.00	3.00	2.00	6.00	2.00	2.00	1.00
Decade 3	3.00	2.00	3.00	4.00	1.00	2.00	2.00	2.00	1.00	1.00	0.00	1.00	2.00
Decade 4	5.00	3.00	3.00	2.00	2.00	0.00	4.00	3.00	3.00	3.00	1.00	3.00	3.00
Decade 5	3.00	2.00	3.00	6.00	3.00	3.00	3.00	3.00	2.00	2.00	1.00	5.00	1.00
# Sign. CC	3.60	2.60	3.60	3.60	1.80	2.40	3.40	2.40	2.00	2.80	1.20	3.00	1.60

Panel D: 104 Own Constructed Anomalies

	mkt	smb	hml	mom	rmw	cma	WMP	mgmt	perf	r_me	r_ia	r_roe	r_eg
Avg. T	2.14	1.52	2.35	2.89	2.44	1.40	1.76	1.62	1.82	1.27	1.21	1.93	1.80
Avg t (Sig. CC)	2.41	1.57	2.69	3.36	2.74	1.55	1.92	1.81	2.03	1.28	1.32	2.13	2.00
Decade 1	2.00	4.00	5.00	5.00	4.00	4.00	5.00	2.00	5.00	1.00	1.00	2.00	2.00
Decade 2	4.00	4.00	4.00	4.00	5.00	2.00	2.00	1.00	3.00	4.00	3.00	3.00	4.00
Decade 3	5.00	3.00	6.00	2.00	5.00	1.00	5.00	5.00	1.00	1.00	3.00	2.00	5.00
Decade 4	5.00	2.00	4.00	7.00	5.00	3.00	5.00	3.00	5.00	4.00	3.00	4.00	4.00
Decade 5	5.00	2.00	3.00	5.00	4.00	3.00	2.00	3.00	2.00	3.00	2.00	6.00	4.00
# Sign. CC	4.20	3.00	4.40	4.60	4.60	2.60	3.80	2.80	3.20	2.60	2.40	3.40	3.80

Panel E: 2190 Own Constructed Nonlinear Portfolios

	mkt	smb	hml	mom	rmw	cma	WMP	mgmt	perf	r_me	r_ia	r_roe	r_eg
Avg. T	7.45	1.84	1.86	2.76	1.40	1.28	1.63	1.52	1.35	1.40	1.26	1.44	1.27
Avg t (Sig. CC)	11.00	2.38	2.46	3.90	1.77	1.50	2.06	1.81	1.72	1.73	1.50	1.79	1.47
Decade 1	4.00	3.00	5.00	5.00	2.00	4.00	4.00	1.00	3.00	2.00	4.00	1.00	1.00
Decade 2	4.00	3.00	3.00	5.00	2.00	1.00	3.00	3.00	2.00	2.00	1.00	4.00	3.00
Decade 3	3.00	2.00	3.00	3.00	2.00	3.00	2.00	4.00	1.00	1.00	1.00	0.00	4.00
Decade 4	6.00	2.00	2.00	5.00	4.00	0.00	3.00	4.00	3.00	4.00	2.00	5.00	2.00
Decade 5	4.00	5.00	3.00	5.00	3.00	3.00	0.00	4.00	4.00	5.00	4.00	4.00	2.00
# Sign. CC	4.20	3.00	3.20	4.60	2.60	2.20	2.40	3.20	2.60	2.80	2.40	2.80	2.40

Table B2
Protocol Step 2: Two-Pass Regressions

This table presents the results from the second step (sufficient condition) of the protocol in Pukthuanthong, Roll, and Subrahmanyam, 2019. Test assets include 118 long-minus-short portfolios from Hou, Xue, and Zhang (2020) in Panel A, 1173 single-sorted portfolios from Hou, Xue, and Zhang (2020) in Panel B, 360 ML-based nonlinear portfolios from Bryzgalova, Pelger, and Zhu (2020) in Panel C, 104 own constructed anomalies in Panel D, and 1173 own constructed nonlinear portfolios in Panel E. "*WMP*" is the *War* mimicking portfolio; "mkt, smb, hml, rmw, cma, mom" are Fama and French (2018)'s six factors; "mkt, smb, mgmt, perf" are Stambaugh and Yuan (2017)'s mispricing factors; and "r_mkt, r_me, r_ia, r_roe, r_eg" are Hou, Mo, Xue, and Zhang (2021)'s Q5 factors. The sample is from January 1967 to December 2016.

	118 LMS Anomalies	1173 Single Sorted Portfolios	360 Tree-Based Nonlinear Portfolios	104 Own Constructed Anomalies	2190 Own Constructed Nonlinear Portfolios
Intercept	0.001***	0.001	-0.003	-0.004***	0.007***
	[5.540]	[0.410]	[-0.800]	[-11.730]	[3.420]
mkt	0.011***	0.005	0.005*	0.006**	0.003
	[3.400]	[1.640]	[1.680]	[2.330]	[1.530]
smb			0.003		0.004*
			[1.640]		[1.740]
hml	0.006***	0.004***	-0.007***	0.004***	0.000
	[3.580]	[2.590]	[-4.020]	[2.790]	[0.080]
mom	0.006***	0.005**	0.007***	0.006***	0.007***
	[2.850]	[2.490]	[3.470]	[2.990]	[3.110]
rmw	0.002	0.001		-0.001	
	[1.360]	[0.690]		[-0.520]	
WMP	-0.003*	-0.002	-0.029***	-0.002*	-0.011***
	[-1.810]	[-1.130]	[-13.200]	[-1.660]	[-5.930]
mgmt	0.006***	0.002		0.003*	
	[3.970]	[1.070]		[1.910]	
perf		0.006***		0.013***	
		[2.940]		[5.850]	
r_roe	0.004***	0.003***	0.005***	0.000	
	[3.210]	[2.740]	[2.700]	[0.050]	
r_eg	0.008***	0.006***		0.009***	
	[7.380]	[5.740]		[6.520]	
R^2	0.529***	0.319***	0.620***	0.486***	0.336***

C Details on Portfolio Construction

C.1 104 Own Constructed Anomalies

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

Table C1
104 Own Constructed Anomalies

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

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

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

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

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

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

C.2 2190 Own Constructed Nonlinear Portfolios

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

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

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

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

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

[2] We standardize characteristics firm by firm in each time to avoid look-ahead bias and prevent the mis-ranking issue.

[3] We sort stocks into deciles based on transformed characteristics above and calculate the average returns next period by group and assign them to the corresponding characteristics and decile (for example, X1_1).

[4] We create long-short portfolios, i.e., portfolios ten minus one for each transformed characteristic.

[5] We use 360 ML-based nonlinear portfolios developed by Bryzgalova, Pelger, and Zhu (2020) (see Appendix C.3 for the list and description).[4] These portfolios can capture the higher dimensional nonlinear information from characteristics.

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

Table C2
2190 Own Constructed Nonlinear Portfolios

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

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

C.3 360 ML-based Nonlinear Portfolios

This subsection shows 360 ML-based nonlinear portfolios for each characteristics groups, each containing ten decile portfolios. See Bryzgalova, Pelger, and Zhu (2020) for the detailed construction and the following tables for variable descriptions.

Table C3
360 ML-based Nonlinear Characteristics Groups

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

Table C4
10 ML-based Characterisrics

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