Essays on Empirical Asset Pricing

by

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To my parents and my wife.

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Abstract

This thesis is a collection of three essays corresponding to the three research projects I undertook in the area of empirical asset pricing and institutional investors.

In the first essay, we show that a simple and intuitive variable, the return of a bear spread portfolio orthogonalized with respect to the market (H-Bear factor), can serve as an important pillar for explaining the cross-section of hedge fund returns. Low H-Bear exposure funds (bear risk insurance sellers) outperform high H-Bear exposure funds (bear risk insurance buyers) by 0.58% per month on average, outperform even during market crashes, but underperform when bear market risk materializes. Overall, we identify a new risk dimension that affects hedge fund performance, and we show that this risk factor is distinct from the already popular realized tail risk.

The second essay analyzes the impact of firm-level political risk on individual equity option. We document a political risk premium of about 0.30% per month in the equity option market. High-political risk firms exhibit delta-hedged option returns that are significantly lower than those of low-political risk firms. The effect holds both in a cross-sectional and in a time-series context. Further, the political risk-option return relation is more pronounced among firms with high option demand, high information asymmetry, and high default probability, while it is mitigated for politically active firms. The demand pressure for the options of politically risky firms is driven by the call purchases of public customers and the put purchases of firm proprietary investors. Hence, it appears that due to its heterogeneous nature firm-level political risk is treated differently by different investor groups.

In the third essay, we investigate the effect of climate change exposure on mutual fund performance. In the presence of rising concern about climate change that potentially affects risk and return of investors' portfolio companies, active investors might have dispersed climate risk exposures. We compute mutual fund covariance with market-wide climate change news index and find that high (positive) climate beta funds outperform low (negative) climate beta funds by 0.24% per month on a risk-adjusted basis. High climate beta funds tilt their holdings toward stocks with high potential to hedge against climate change. In the cross section, such stocks yield higher excess returns, which are driven by greater pricing pressure and superior financial performance over our sample period.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Understanding the behavior of asset prices is crucial to many important decisions, not only for institutional investors but also for most people in their daily lives. For instance, the choice of asset allocation in the form of cash, bonds, stocks, options or alternative assets such as hedge funds depends on investors' expectation of risks and returns associated with these different forms of investments. Therefore, in the following chapters, we attempt to gain new insights into the risk-return behavior of various types of financial assets, ranging from hedge funds, options to mutual funds.

In **Chapter 2**, we focus on hedge fund performance. During the period over 1990-2021, the hedge fund industry grew at a dramatic pace, with the total asset under management (AUM) increasing from \$39 billion in 1990 to more than \$4.53 trillion in 2021. Despite its increasing importance, the task of explaining hedge fund returns is very challenging because hedge fund industry is loosely regulated with limited data availability. Earlier studies in this area focus on the performance comparison between hedge funds and mutual funds, concluding that hedge funds employ more dynamic trading strategies that involve the use of derivatives, short-selling and leverage; thus, they have a higher level of risks and earn higher risk-adjusted returns (Ackermann, McEnally and Ravenscraft, 1999; Liang, 1999). Continuing from the studies on hedge fund-mutual fund comparison, many scholars attempt to explain hedge fund returns in both the time-series and the cross-sectional context with a focus on the link between the performance of hedge funds and their (non-linear) risk exposure, managerial skills and factor timing ability.

Our Chapter 2 contributes to the hedge fund performance literature by showing that a simple and intuitive variable, the return of a bear spread portfolio orthogonalized with respect to the market (H-Bear factor), can serve as an important pillar for explaining the cross-section of hedge fund returns. The H-Bear factor carries a sizeable bear risk premium that is paid to hedge concerns of future market crashes. We find that low H-Bear exposure funds (bear risk insurance sellers) outperform high H-Bear exposure funds (bear risk insurance buyers) by 0.58% per month on average, outperform even during market crashes, but perform worse when bear market risk realizes. In our framework, the persistent spread between the funds with low and high H-Bear exposure reflects the bear risk premium. And such spread does not require any skills in trading over-priced "fear premium" or that the Bear sellers possess superior market timing ability than the buyers as in Gao, Gao and Song (2018). We also challenge the conventional wisdom which associates the returns of insurance-like hedge fund strategies with realized market tail risk. We show that while both Bear buyers and sellers perform poorly during market crashes, Bear buyers experience greater losses for paying the bear risk premium on top of the tail risk. Overall, our study sheds light to a new and potentially important risk perspective in explaining hedge fund performance.

In **Chapter 3**, we move our focus to option market and investigate whether and how firm-level political risk affects individual option returns. In fact, there is an emerging stream of literature that examines the effect of political uncertainty on financial markets. One channel through which political risk impacts asset prices is that it increases external investors' risk perception. Pastor and Veronesi (2012, 2013) build a theoretical foundation for the pricing of political risk and show that investors demand a premium for bearing this risk. Their theory has been empirically supported through analysis of various financial assets such as stock, credit, option, CDS, and commodity (Belo et al., 2013; Brogaard and Detzel, 2015; Baker et al., 2016; Kelly et al., 2016; Liu et al., 2017; Liu and Zhong, 2017; Wang et al., 2019; Kaviani et al., 2020; Hou et al., 2020). For example, Kelly et al. (2016) find that index options whose lives span political events such as national elections and global summits tend to be more expensive as they provide protection against the risks associated with those events. However, given the difficulty of measuring political risk at the firm-level, most existing studies investigating the financial market outcomes of political risks rely on election events or the market-wide political risk that masks a large proportion of the variation in political risk across firms and overtime.

Using a text-based measure of firm-level political risk extracted from quarterly conference calls, we document a political risk premium of about 0.30% per month in the equity option market. High-political risk firms exhibit delta-hedged option returns that are significantly lower than those of low-political risk firms. We show that the effect holds both in a cross-sectional and in a time-series context. Our finding implies that investors are willing to pay higher option prices to hedge or speculate against firm-specific political uncertainty, thus resulting in lower option returns. We show that the pricing effect comes from both demand and supply sides as well as the rational incorporation of political risk in the stochastic discount factor. In this respect, we document that the effect of political risk on option returns is more pronounced among firms with high option demand pressure, high information asymmetry and high default risk.

In **Chapter 4**, we explore the sustainable investing implication for mutual fund performance. Along with the growing awareness of corporate social responsibility issues, sustainable and responsible investments (SRI) have become part of the mainstream investing strategies. According to the *2020 Report on Sustainable and Impact Investing Trends*, the sustainable investing industry in the US has grown more than 25-fold since 1995, reaching $17.1 trillion – or 1 in 3 dollars – of the total US assets under professional management. Besides, one central focus of sustainable investing is climate change concern. Survey on institutional investors indicates that climate risks have important financial implications for their portfolio firms and many investors integrate climate risks into their investment processes (Krueger, Sautner, and Starks, 2020). Therefore, it is important to examine how the incorporation of climate change concern affects the performance of active mutual funds.

We propose a new measure to identify mutual funds that are positively or negatively affected by climate change concern. Specifically, we use fund-level climate beta, i.e., the sensitivity of each mutual fund returns to innovations in climate change news index, to capture the fund's ability to hedge against climate change and show that high climate beta funds outperform low climate beta funds both in raw and in risk-adjusted return basis. The outperformance stems from funds tilting their portfolios towards high climate beta stocks, i.e., stocks with better climate-hedging potential. We verify the characteristics of these stocks by documenting that they are meaningfully related to the measure of firms' climate exposure and the improvement in firms' environmental performance. Moreover, these stocks experience a significant increase in value, which is driven by better financial performance and increasing investor demand. Such price appreciation benefits funds that tilt their investments toward these stocks. Overall, this chapter documents an important financial implication regarding the integration of climate concern into investors' investment processes.

Chapter 5 provides a concluding remark, identifying our limitations and providing possible directions for future research.

Chapter 2

Bear factor and hedge fund performance

2.1. Introduction

Building on Lu and Murray's (2019) insight, we document that a new market-hedged bear factor (H-Bear) can effectively explain a large proportion of the variation in the cross-section of hedge fund returns.[1] The H-Bear factor carries a negative bear risk premium (–1.09% per month, t-statistic = –6.77) which compensates for the change in ex-ante risk-neutral probability of future bear market states, rather than the physical probability of bear market states.[2] The economic intuition behind the negative premium is that assets that pay off when there is an increasing probability or concern about future bear market states should earn lower average returns because they serve as hedging instruments. Specifically, this premium is paid the hedge against the *change* in ex-ante downside or tail risk, as opposed to the tail risk level.

In our empirical analysis, we measure H-Bear exposure for each hedge fund in each month by regressing its excess returns on the H-Bear factor over a 24-month rolling window. Then we sort hedge funds based on their exposure to the H-Bear factor, i.e., H-Bear beta, group them into

[1]Lu and Murray (2019) highlight that bear market risk, as captured by the return of a bear spread portfolio hedged with respect to the market return, is priced in the stock market.

[2]H-Bear factor is constructed using S&P 500 index options in the following way: We go long an out-of-the-money (OTM) put and short a further OTM put, so that the overall position pays off $1 when the S&P 500 index is 1.5 standard deviations below its forward price. The return of this portfolio is regressed against the market return and the residuals from this regression constitute the H-Bear factor. More details are provided in Section 2.2.

quintiles, and examine the average returns of these quintiles over the next one month. Remarkably, hedge funds in the lowest H-Bear beta quintile ("Bear sellers") outperform those in the highest H-Bear beta quintile ("Bear buyers") by 0.58% per month (*t*-statistic = 3.53) on average. Such outperformance exists even during bad times (i.e., market crashes), confirming that the H-Bear factor risk premium is distinct from the well-known tail risk premium. The risk-adjusted return spread between the high and low H-Bear beta quintiles remains significant based on the Fung and Hsieh (2004) seven-factor model as well as other performance evaluation models used in the asset pricing literature. Our results also survive various robustness checks, namely using value-weighted portfolios, unsmoothed returns, and different hedge fund databases, among others, while the predictive power of H-Bear factor loading for future hedge fund returns extends as far as 18 months ahead. Moreover, a Fama-MacBeth (1973) regression analysis demonstrates that the H-Bear beta effect remains particularly robust when controlling for a large set of alternative hedge fund characteristics and exposures to various other risk factors. Overall, our empirical evidence suggests that the H-Bear factor is arguably one of the strongest hedge fund return predictors that have appeared in the literature.[3]

In a recent study, Gao, Gao, and Song (2018) suggest that certain hedge funds possess skills in exploiting overpriced ex-ante market disaster risk concerns, and thus persistently outperform other hedge funds. By adopting an alternative measure of innovations in ex-ante bear market concerns, we offer a risk-based explanation of hedge fund returns. In our framework, the persistent spread between the funds with low and high H-Bear exposure reflects the bear risk premium. And such spread does not require any skills in trading over-priced "fear premium" or that the Bear sellers

[3]There are a few potential reasons why the H-Bear factor could exhibit strong explanatory power for hedge fund returns. One is that hedge funds are known to trade bear-spread portfolios and other option portfolios or using complicated strategies with option-like payoffs (Agarwal and Naik, 2004; Aragon and Martin, 2010; Lu and Murray, 2019). Another reason is that the H-Bear factor provides an effective way to quantify hedge funds' hedged positions, while the previous literature is unable to do so because it mainly focuses on using unhedged call or put options to evaluate hedge fund performance.

possess superior market timing ability than the buyers. Our study, therefore, contributes a new and potentially important risk perspective in explaining hedge fund performance.

In another seminal paper, Agarwal, Ruenzi, and Weigert (2017) show that hedge funds with high market tail risk outperform hedge funds with low tail risk on average but underperform in periods of negative market returns. Moreover, they posit that tail risk arises naturally because several popular hedge fund trading strategies resemble writing out-of-the money put options on the equity market index. This has given rise to a conventional wisdom which suggests that certain hedge funds tend to act more as insurance sellers, collecting an insurance premium in good market periods (i.e., in most of the cases) and experiencing substantial losses in bad market periods (i.e., in a few cases). However, it is noteworthy that the overall market tail risk of each hedge fund stems from the amalgamation of a large set of different trading strategies. For example, while it is possible that a hedge fund exhibits high tail risk because a large part of its portfolio consists of strategies that resemble insurance provision, it is also likely that a hedge fund exhibits similarly high tail risk because it only partially hedges a portfolio that is overly exposed to market crashes. Obviously, the asset pricing implications of the two cases are different.

In addition, the direct link between market tail risk and the returns of insurance-like strategies requires that the two have an (almost) perfect negative correlation. Following Lu and Murray (2019), we confirm that this correlation is far from perfect. In particular, it is possible that there is a high increase in investors' fears about future bear market states even if there is little or no negative market return. In this case, the gain (loss) for the insurance buyer (seller) is high. In the same vein, it is possible to have little increase in the price of market insurance even if there is a large negative market return. In such a case, the buyer (seller) is actually worse off (better off). Overall, our study challenges the conventional wisdom which directly and consistently associates the returns of insurance-like hedge fund strategies with realized market crashes. Instead, it reveals a new risk premium that reflects the change in insurance price (or alternatively the change in ex-ante concerns about future bear market states) after cleansing it of the effect of realized market returns.

We delve into the economic nature of the H-Bear factor's predictive ability by showing that during market crashes both high and low H-Bear beta funds earn negative excess returns.[4] Notably, high H-Bear beta funds experience greater losses, consistent with the H-Bear factor being negative rather than positive during the most negative market return periods. This is an important result that differentiates our H-Bear factor from realized tail risk and highlights its unique information content (i.e., the H-Bear factor is related to the change in tail risk, rather than the tail risk level).

In addition, we find further evidence supporting the risk-based explanation of the H-Bear factor's predictive power. If low H-Bear beta funds earn higher returns on average by being exposed to bear market risk, we should observe an opposite, i.e., positive, relation between H-Bear beta and hedge fund returns during periods of high bear market risk, i.e., when there is an increase in concerns about future bear market states. We define high bear market risk periods as months when the H-Bear factor is positive. In such cases, the increase (decrease) in the price for market insurance is higher (lower) than what would be justified by the concurrent negative (positive) market return. We observe a strong *positive* relation between H-Bear beta and future hedge fund returns during these months. In contrast, during the remaining months, the relation is negative and statistically significant. Collectively, our findings lend further support to the idea that in the cross-section those hedge funds that are exposed to bear market risk are not necessarily always more exposed to realized market tail risk.

We next investigate potential trading strategies that may serve as sources of exposure to the H-Bear factor. First, we construct feasible put option strategies in the spirit of Jurek and Stafford (2015) and show that, as expected, low H-Bear beta can be associated with a naked put-writing strategy, while high H-Bear beta can be associated with a protective put-buying strategy. Second, we show that H-Bear beta is significantly affected by the sensitivity to a trading portfolio that goes long low bear beta stocks and short high bear beta stocks, implying that low H-Bear beta hedge

[4]The finding is also consistent with the notion that hedge fund industry as a whole is exposed to substantial market downturns.

funds are likely buyers of low bear beta stocks, whilst high H-Bear beta hedge funds are likely buyers of high bear beta stocks.

Finally, we examine the characteristics of hedge fund H-Bear exposure. Several findings are in line with prior evidence on the risk-taking behavior of hedge funds. For example, low H-Bear beta is associated with funds that are young, exhibit negative return skewness, and have higher past return. The results support the notion that young funds might have an incentive to attract fund flows by establishing a track record of high returns early in their life cycle. In addition, funds with low H-Bear beta are more likely to demand higher management fees and have a hurdle rate, which is consistent with risk-taking behavior responding to incentives. It is important to note that while certain hedge fund characteristics help us understand the driving forces of the H-Bear sensitivity, none of them subsumes the relation between H-Bear beta and future fund returns.

A distinctive feature of our study when compared to Gao, Gao, and Song (2018) is that it relies on the innovations in bear concerns (a risk-based perspective) instead of the current level of bear concerns (a skill-based perspective). Specifically, Gao, Gao, and Song's (2018) RIX measure uses the average daily price of a put option portfolio within a month rather than the monthly return. Intuitively, funds with high sensitivity to RIX exhibit high returns when the level/price of disaster concerns is high, and hence are considered skilled and are shown to persistently outperform other funds. We find that if we follow our approach and use the sensitivity to the return – and not to the price level – of the same S&P 500 index put portfolio that is used in the RIX construction, this sensitivity predicts future hedge fund returns negatively rather than positively. Importantly, the hedge fund sensitivity to this "RIX return" factor and the RIX betas do not subsume each other in predicting future hedge fund returns. Overall, the conclusions of the two studies are not inconsistent with each other. It is perfectly possible that the two effects, i.e., insurance sellers exploiting cases of overpriced insurance as Gao, Gao, and Song (2018) suggest and insurance sellers earning high returns by just being exposed to bear market risk as we suggest, coexist and complement each other.

Our study is related to a small but burgeoning literature that investigates the ability of various option-implied risk factors to explain the cross-section of hedge fund returns.[5] Specifically, Agarwal, Bakshi, and Huij (2010), Buraschi, Kosowski, and Trojani (2014), and Agarwal, Arisoy, and Naik (2017) show that the higher order risk-neutral moments, correlation risk and volatility-of-volatility of the stock market, respectively, have significant explanatory power for future hedge fund returns. More generally, our study is related to a series of studies that utilize the risk profile of hedge funds in order to explain their subsequent performance. Bali, Gokcan, and Liang (2007) document a positive relation between value-at-risk and future fund returns, Bali, Brown, and Caglayan (2011) show that the exposures to default premium and to inflation are significant predictors of hedge fund returns, Bali, Brown, and Caglayan (2012) show that funds with higher systematic risk are more profitable, while Bali, Brown, and Caglayan (2014) find that macroeconomic risk is priced in the cross-section. We contribute to the above two strands of the literature by proposing a novel option-implied predictor of hedge fund returns, i.e., the sensitivity to the H-Bear factor, and unravelling the economic mechanism that associates this type of bear risk exposure with fund performance.

The rest of this chapter is organized as follows. Section 2.2 discusses the data, the construction of the Bear portfolio, and the estimation of the hedge fund sensitivity to the H-Bear factor. Section 2.3 presents our main results by studying the effect of H-Bear sensitivity on future hedge fund returns, investigating the predictability across different states of nature, and examining the determinants of H-Bear factor exposure. Section 2.4 provides additional analyses. We perform a series of robustness checks in Section 2.5 and conclude in Section 2.6.

[5]In a different context, a series of studies, such as Fung and Hsieh (1997), Fung and Hsieh (2001), Amin and Kat (2003), Agarwal and Naik (2004), Agarwal, Bakshi, and Huij (2010), Jurek and Stafford (2015), and Agarwal, Arisoy, and Naik (2017), demonstrate option-like features inherent in the time-series return behaviour of many hedge fund investment styles.

2.2. Data and variable construction

2.2.1. Hedge fund data

Hedge fund data, including monthly hedge fund returns and fund characteristics, are from the Hedge Fund Research database (HFR), which is one of the leading sources of hedge fund information.[6] In this database, we originally have information on a total of 25,976 live and defunct hedge funds. Since we construct the Bear portfolio returns using option data from OptionMetrics that are available from January 1996, the full sample period of hedge fund returns that we use in this study is from January 1996 to December 2017. Following the literature, we retain monthly-filing funds and funds that report returns net of all fees and in US dollars.

Next, we make efforts to minimize the effects of potential data biases documented in the hedge fund literature (Fung and Hsieh, 2000; Liang, 2000; Edwards and Caglayan, 2001). First, to mitigate the backfilling bias, we follow Kosowski, Naik, and Teo (2007) to eliminate the first 12 months of a fund's return series. Furthermore, since this problem might be prevalent among small funds, we discard all funds with less than \$10 million of asset under management (AUM). Specifically, if a fund begins with less than \$10 million but later has \$10 million in AUM, we include the fund in the sample from the time its AUM reaches \$10 million and keep it in the sample as long as the fund exists regardless of its AUM. Second, monthly return histories of both live and defunct funds over the sample period are included, which helps minimize the survival bias. In Section 2.5, we perform a robustness check where we assume that returns of drop-out funds are –100% following their last reporting month.

The above process leaves us with a final sample of 11,084 distinct hedge funds, of which 8,190 are defunct funds and the remaining 2,894 are live funds. More specifically, the period 1996–2007 experienced an exponential increase both in number of operating hedge funds, from 764 in 1996 to 4,583 funds at the end of 2007, and in total AUM, from around \$109 billion in 1996 to \$1,549

[6] We provide robustness checks of our main results using EurekaHedge and Lipper TASS databases in Section 2.5.

billion in 2007. However, there was a sharp reversal in both of these figures starting in 2008 due to the financial crisis. By the end of 2017, there were 2,894 operating hedge funds with a total AUM of $1,211 billion in our sample.

We follow Joenväärä, Kauppila, Kosowski and Tolonen (2021) to categorize hedge funds into ten primary strategies: event-driven, relative value, long-short equity, global macro, CTA, equity market-neutral, multi-strategy, short-bias, sector, and fund of funds. In terms of the number of funds, long-short equity is the largest strategy style, comprising 2,936 distinct hedge funds in our sample, whereas there are only 60 hedge funds falling into the short-bias strategy group. Table 2.1 presents descriptive statistics for our hedge fund sample.

[Insert Table 2.1 here]

Panel A of Table 2.1 reports the time-series average of the monthly cross-sectional mean, standard deviation, and percentiles of all individual hedge fund returns. On average, a fund earns 0.64% per month over the sample period with a standard deviation of 4.03%. Among the ten main strategy categories, sector and long-short equity are the two strategies that yield the highest average monthly returns, 0.97% and 0.78% respectively, while short-bias hedge funds realize the lowest performance with an average return of –0.15%.

Panel B reports distribution statistics of cross-sectional hedge fund characteristics. The average AUM of individual hedge funds in our database is $175.22 million, while the median size is $52.31 million, implying that there are a few hedge funds with very large size. On average, an individual hedge fund operates for approximately 78 months or 6.5 years. Management fee and incentive fee are 1.44% and 15.78% on average, respectively. Hedge funds in our sample have an average lockup period of 3.46 months and require an average minimum investment of $1.26 million.

2.2.2. Bear portfolio

2.2.2.1. Data

Data for S&P 500 index options, including daily closing bid and ask quotes, trading volume and open interest for the period from January 1996 to December 2017, are obtained from OptionMetrics. We further collect the daily S&P 500 index level and dividend yield, the VIX index level, and the risk-free rate. We apply several filters to the option data. First, to avoid illiquid options, we discard options if open interest is zero or missing, if the bid quote is zero, or if the bid quote is larger than the ask quote. Second, all options that violate no-arbitrage conditions are excluded. Specifically, for a put option we require that the exercise price exceeds the best bid, which is in turn higher than $max(0, K - S_0)$, where K and S_0 are the option's strike price and the closing level of the S&P 500 index respectively. Third, we only keep options with standard expiration dates.

We use the mid-point of the bid and ask quotes as a proxy for the market price of the option contract. We further define the S&P 500 index forward price to be $F = S_0 e^{(r-y)T}$, where r is the continuously compounded risk-free rate, y is the dividend yield of the S&P 500 index, and T is the time to maturity.

2.2.2.2. Bear portfolio construction

We follow Lu and Murray (2019) and define an Arrow-Debreu bear security as a portfolio that pays $1 when the S&P 500 index level on a given date is in a bear state, and zero otherwise. We approximate this payoff structure from traded options by taking a long position in a put contract with strike price $K_1 > K_2$ and a short position in a put contract with strike price K_2. After scaling both positions by $K_1 - K_2$, the Bear portfolio will generate a payoff of $1 at expiration if the index level is below K_2 and zero if the index level is above K_1. The payoff decreases linearly from $1 to zero for index levels at expiration falling between K_2 and K_1. Thus, the Bear portfolio price, P_{BEAR}, is:

$$P_{BEAR} = \frac{P(K_1) - P(K_2)}{K_1 - K_2}, \tag{2.1}$$

where $P(K)$ is price of a put option with strike price K.

We choose K_2 to be 1.5 standard deviations bellow the S&P 500 index forward price. The strike price K_2 establishes the bear region boundary, meaning that the market is in bear state when the market excess return is more than 1.5 standard deviations below zero.[7] K_1 is set to be one standard deviation below the S&P 500 index forward price.[8]

The standard deviation of the market return is defined as $V\sqrt{T}$, where V is the VIX index level divided by 100. Setting the standard deviation equal to VIX instead of using a constant volatility means that the bear market region under consideration is always adjusted for current market volatility levels. As a result, the price of the Bear portfolio, i.e., the discounted risk-neutral probability of a bear market outcome, remains roughly the same at each portfolio formation period. The return of the portfolio captures innovations in bear market concerns.

In the same vein with Lu and Murray (2019), we define $P(K_1)$ and $P(K_2)$ to be the trading-volume weighted average price of puts with strike prices within a 0.25 standard deviation range of the target strikes, K_1 and K_2. We follow this procedure because traded option contracts with exact targeted strikes are unlikely to exist. In addition, the volume-weighted average put price over a range of strikes gives more weight to liquid put options whose prices are expected to be less affected by microstructure noise. More specifically, we take:

$$P(K_1) = \sum_{K \in \left[Fe^{-1.25\frac{VIX}{100}\sqrt{T}},\ Fe^{-0.75\frac{VIX}{100}\sqrt{T}} \right]} P(K)w(K) \tag{2.2}$$

[7]The 1.5 standard deviations point is chosen based on a trade-off between our objective of capturing significant downward market movements on the one hand, and the relative illiquidity of deep-out-of-the-money put options on the other hand. In Section 2.5, we show that the findings are very similar if we use different definitions of bear market regions.

[8]Although as K_1 approaches K_2, the payoff function of the Bear portfolio converges to the theoretical payoff of an Arrow-Debreu security, the spread between $P(K_1)$ and $P(K_2)$ also converges to zero and might be adversely affected by noise from option bid-ask spreads. Choosing $K_1 - K_2$ to be half a standard deviation is based on a trade-off between these two considerations.

and

$$P(K_2) = \sum\nolimits_{K \in \left[Fe^{-1.75\frac{VIX}{100}\sqrt{T}},\ Fe^{-1.25\frac{VIX}{100}\sqrt{T}} \right]} P(K)w(K)\,, \tag{2.3}$$

where $w(K)$ is the trading volume of a put option with strike price K divided by the total trading volume of all put options in the indicated range.

2.2.2.3 Bear portfolio returns and H-Bear factor

Since returns of individual hedge funds in our database are available on a monthly basis, we also create a monthly Bear portfolio return factor. Specifically, on the last trading day of each month from January 1996 to November 2017, we buy the Bear portfolio using put options that have the shortest maturity among those with more than one month to expiration and calculate its price using the averages of closing bid-ask quotes of these options.[9] We hold the portfolio for one month and measure its excess return by subtracting the one-month risk-free rate from the one-month buy-and-hold return. In total, there are 264 monthly Bear portfolio excess returns for the period over 1996–2017.

[Insert Table 2.2 here]

Panel A of Table 2.2 reports the descriptive statistics for the monthly times-series of the Bear factor. Following Lu and Murray (2019), we scale the Bear factor to have the same volatility with the market factor. The average monthly excess return of the Bear factor is –1.64% and is statistically significant with a t-statistic of –5.04 (as shown in the first column in Panel B of Table 2.2).

We further investigate whether the significantly negative Bear portfolio excess return is just simply the compensation for exposure to the market factor. In Panel B of Table 2.2, we perform a

[9]For example, on 31/01/1996 we choose options that expire on 16/03/1996 to create the Bear portfolio. Out of 264 months, there are nine months for which we do not have available put options that meet these requirements. For these months, we form the Bear portfolio on the first trading day of the month (instead of the end of last month) and hold it until the month end.

time-series regression of the Bear factor, $r_{BEAR,t}$, on the contemporaneous market excess returns, MKT_t, over January 1996 to December 2017. The regression is defined as:

$$r_{BEAR,t} = \gamma + \delta \times MKT_t + \varepsilon_t, \tag{2.4}$$

where δ captures the exposure of the Bear portfolio to the market and γ measures the average Bear portfolio excess return that is not explained by the market risk.

Consistent with its negative delta exposure, the Bear portfolio exhibits a significant market exposure with a coefficient on the market factor of –0.85 (t-statistic = –15.90) and an adjusted R^2 of 72%. Noticeably, the average adjusted return after controlling for the market factor is –1.09% per month and is statistically significant with a t-statistic of –6.77. The finding implies that market factor exposure cannot fully capture the negative average return of the Bear portfolio.[10] In other words, selling the market-hedged Bear (H-Bear) portfolio:

$$r_{H-BEAR,t} = \gamma + \varepsilon_t = r_{BEAR,t} - \delta \times MKT_t, \tag{2.5}$$

is accompanied by a significant premium on average. Intuitively, the H-Bear factor is the component of the Bear portfolio return that is orthogonal to (or hedged with respect to) the market return, i.e., the intercept plus the residuals from a regression of the Bear portfolio returns on the market returns.

2.2.3. Hedge fund exposure to the H-Bear factor

Motivated by the negative premium of the market-hedged Bear portfolio and the "hedge" role of hedge funds, at the end of each month from December 1997 to November 2017 and for each hedge fund, we measure the hedge fund's exposure to the H-Bear factor by running the following time-series regression over a 24-month rolling window:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{H-BEAR} \times r_{H-BEAR,t} + \epsilon_{i,t}, \tag{2.6}$$

[10]In an unreported analysis, we find that the Bear factor is not subsumed by other standard risk factors in the asset pricing and hedge fund literature (e.g., value, size, momentum, as well as the Fung and Hsieh (2004) seven factors).

where $r_{i,t}$ is the excess return of fund i in month t, and $r_{H-BEAR,t}$ is the H-Bear factor return estimated as per Equations (2.4)-(2.5) over the same 24-month window. We require at least 18 months of non-missing fund returns to ensure that we have a sufficient number of observations in the estimation. Note that the above regression provides exactly the same H-Bear beta, $\beta_{i,t}^{H-BEAR}$, with the following two-factor model:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{BEAR,t} + \epsilon_{i,t}, \qquad (2.7)$$

where MKT_t is the CRSP value-weighted market excess return, and $r_{BEAR,t}$ is the return of the plain Bear portfolio.

By combining Equations (2.5) and (2.7) we get:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{H-BEAR,t} + \epsilon_{i,t}. \qquad (2.8)$$

where $\beta_{i,t}^{MKT} = \left(\beta_{i,t}^{M} + \beta_{i,t}^{H-BEAR} \times \delta\right)$ captures the hedge fund's unhedged market exposure (i.e., market beta). In this way, the total risk exposure of a hedge fund can be seen as the combination of its unhedged market exposure and its exposure to the H-Bear factor.

[Insert Table 2.3 here]

Panel A of Table 2.3 presents the average $\beta_{i,t}^{H-BEAR}$ and $\beta_{i,t}^{M}$ of portfolios sorted on H-Bear beta. We find that there is a high dispersion in H-Bear betas among hedge funds, ranging from an average of –0.55 in the first quintile to an average of 0.53 in the fifth quintile. Because the Bear portfolio is considered as a market insurance, by construction, high (positive) H-Bear beta hedge funds act as insurance buyers, while low (negative) H-Bear beta hedge funds act as insurance sellers. We observe that the Bear buyers have a high β^{M} of 0.89, while the Bear sellers have a slightly negative β^{M} of –0.04. This result is reasonable in the sense that the hedge funds that seek insurance are the ones already having some high exposure to the market. However, these β^{M} values ignore that fact that the market and the Bear portfolio are highly negatively correlated. In fact, an insurance buyer (seller) reduces (increases) his overall market exposure by being long (short) the Bear portfolio.

Panel B of Table 2.3 shows that the average unhedged market exposures, $\beta_{i,t}^{MKT} = \left(\beta_{i,t}^{M} + \beta_{i,t}^{H-BEAR} \times \delta\right)$, of the low and high H-Bear beta hedge funds are almost identical, at 0.43.[11] Collectively, the results can be interpreted as follows. Both Bear buyers and Bear sellers behave as if they are similarly exposed to the market factor, but Bear buyers obtain also a hedged long position to the market, while Bear sellers obtain also a hedged short position to the market. In that respect, any difference in their relative performance should be attributed to their differential exposure to the H-Bear factor. In other words, hedge funds with low H-Bear betas are expected to earn the negative premium of the H-Bear factor, and hence outperform on average the high H-Bear beta hedge funds that pay the premium.

Panel C of Table 2.2 provides summary statistics for the H-Bear factor. Note that in this case the H-Bear factor return for each month t is obtained from a rolling regression of the Bear factor on the market factor over the past 24 months. Therefore, the average H-Bear return is slightly different from the constant term in the second column of Panel B, which was estimated using a full-sample regression. Still, both the average and the median H-Bear factor returns are highly negative, –1.25% and –1.69%, respectively. Panel D of Table 2.2 and Figure 2.1 reveal that the negative premium of the H-Bear factor is distinct from realized tail risk. We find that the average H-Bear return during down and up market periods are respectively –1.41% and –1.16%, while the average market return during periods of positive and negative H-Bear returns are respectively 1.69% and 0.24%. The five highest (positive) market hedged Bear portfolio returns happen in August 1998, September 2000, February 2001, April 2002, and May 2012. During these months, the market excess returns were –16.08%, –5.45%, –10.05%, –5.20%, and –6.19%, respectively. While these returns are all negative, with the exception of August 1998, those months are not the ones that experience the largest market losses. In fact, the average hedged Bear portfolio return in

[11]Note that, while in the regression of Panel A we include the plain Bear factor and in the regression of Panel B we include the H-Bear factor, the respective coefficients are exactly the same because in Panel A we control for the market. Therefore, in Panel A we still use the notation $\beta_{i,t}^{H-BEAR}$. The difference between the two panels is that β^{M} in Panel A can be considered the market exposure of funds before hedging, while β^{MKT} in Panel B can be seen as the market exposure of funds after hedging or the component of the market exposure that remains unhedged.

the five months with the most negative market returns over 1998–2017 is –0.22%, which is negative rather than positive.

[Insert Figure 2.1 here]

These results are indicative of an important observation. While the returns of the market insurance are strongly affected by market movements, these two do not necessarily coincide. It is possible to have little increase in the price of market insurance even if there is a large negative market return. In such a case, the buyer (seller) is actually worse off (better off). In the same vein, it is possible that there is a high increase in investors' fears about future bear market states even if there is little or no negative market return. In this case, the gain (loss) for the insurance buyer (seller) is high. Intuitively, when concerns about future bear market states increase, the increase (decrease) in insurance premium is more (less) than the decrease (increase) in market price, and vice versa. Therefore, the H-Bear factor reflects the increase in investors' concerns about future bear market states on top of what is justified by concurrent market returns. In that respect, the estimated hedge funds' exposures to H-Bear factor are more likely to capture their exposures to the change in tail risk, rather than its level.

There is also a reason for which it is important to control for the market when estimating hedge fund exposure to bear market risk. In particular, if we do not do so, it will be impossible to correctly identify Bear buyers. As discussed above, high H-Bear beta funds have a high positive β^M and the Bear portfolio and the market factor are highly negatively correlated. Therefore, if the market factor is excluded from Equation (2.7) or alternatively if we use the plain Bear portfolio instead of the H-Bear portfolio in Equation (2.6), the large positive exposure of Bear buyers to the market will dominate the positive exposure to the Bear portfolio and the H-Bear beta will turn negative. It is easy to see this by combining:

$$MKT_t = \rho + \lambda \times r_{BEAR,t} + \zeta_t, \tag{2.9}$$

with Equation (2.7) to get:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times \rho + \left(\beta_{i,t}^{H-BEAR} + \beta_{i,t}^{M} \times \lambda\right) \times r_{BEAR,t} + \beta_{i,t}^{M} \times \zeta_t + \epsilon_{i,t}, \qquad (2.10)$$

and noting that λ is typically a number between –0.85 and –0.90, while in the case of Bear buyers the average $\beta_{i,t}^{H-BEAR}$ is equal to 0.53 and the average $\beta_{i,t}^{M}$ is equal to 0.89. In fact, Panel C of Table 2.3 shows that ignoring the market factor would cause the Bear buyers' exposure to the Bear factor, $\beta_{i,t}^{BEAR} = \left(\beta_{i,t}^{H-BEAR} + \beta_{i,t}^{M} \times \lambda\right)$, to become negative, at –0.27. The problem is much less acute in the case of Bear sellers. Their exposure to the Bear portfolio estimated ignoring the market factor takes the value of –0.51, which is similar to the value of –0.55 found when controlling for the market. The reason is that the average $\beta_{i,t}^{M}$ of Bear sellers is close to zero, at –0.04, and hence $\left(\beta_{i,t}^{H-BEAR} + \beta_{i,t}^{M} \times \lambda\right)$ is a number very close to $\beta_{i,t}^{H-BEAR}$.

2.3. H-Bear factor and hedge fund performance

So far, we have shown that any systematic difference in relative performance of Bear sellers and buyers is expected to come from their differential exposure to the H-Bear factor – a proxy for bear market risk. This hedged factor is negative on average and is not correlated with market movements. Hence, we hypothesize that hedge funds with negative H-Bear betas – whose strategies resemble selling insurance – outperform on average by earning the negative premium of the H-Bear factor without being necessarily more exposed to market crashes. Instead, they underperform when bear market risk is high (i.e., when concerns about future bear market states increase).

2.3.1. Portfolio-level analysis

At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles based on their exposure to the H-Bear factor. The fifth (first) quintile consists of funds with the highest (lowest) H-Bear betas. We also form a portfolio that goes long hedge funds in the fifth quintile and short hedge funds in the first quintile. We hold the portfolios for one month and measure their returns, which are from January 1998 to December 2017.[12]

[Insert Table 2.4 here]

Panel A of Table 2.4 reports the results for the performance of hedge fund portfolios sorted by H-Bear beta. In particular, we present the time-series average of hedge fund returns across five quintiles. Each quintile has about 500 hedge funds on average and is well diversified. The average monthly equal-weighted hedge fund portfolio returns decline monotonically from 0.87% in the lowest H-Bear beta quintile to 0.29% in the highest H-Bear beta quintile. The average return difference between quintile 5 and quintile 1 is –0.58% per month, or –6.99% per year, with a t-statistic of –3.53. To measure portfolio-level risk-adjusted returns (i.e., alphas), we perform a time-series regression of the monthly hedge fund portfolio returns in each quintile on the Fung and Hsieh (2004) seven factors, including three trend-following, two equity-oriented, and two bond-oriented risk factors (i.e., FTFSBD, PTFSFX, PTFSCOM, S&P, SCMLC, BD10RET, and BAAMTSY). The regression is generally defined as:

$$r_{P,t} = \alpha_P + \boldsymbol{\beta_P}' \times \boldsymbol{F}_t + \varepsilon_{P,t}, \tag{2.11}$$

where $r_{P,t}$ is month t hedge fund portfolio return in each quintile and $\boldsymbol{F}_t$ is a vector of risk factors. We find that the Fung-Hsieh 7-factor alpha of the lowest H-Bear beta portfolio is 0.70% (with a t-statistic of 4.04) while that of the highest H-Bear beta portfolio is only –0.02% (with a t-statistic of –0.17). The resulting spread between alphas of quintile portfolios 5 and 1 is –0.72% per month and is significant at all conventional levels with a t-statistic of –3.73.

We further examine whether the return spread between quintile 5 and 1 can be explained by additional hedge fund risk factors. We modify Equation (2.11) by regressing equal-weighted Q5–

[12]If H-Bear factor exposure is a characteristic that predicts the cross-section of hedge fund returns, it should display a relative persistence at the fund level. Table A2.2 shows a meaningful difference in the average H-Bear beta between high and low H-Bear beta hedge fund quintiles for a holding horizon of one up to 36 months. The evidence suggests that H-Bear beta is strongly persistent.

Q1 portfolio returns on the Fung and Hsieh (2004) and several additional risk factors. The results are presented in Panel B of Table 2.4.

For ease of comparison, we report the regression result based on the Fung and Hsieh (2004) seven-factor model as our baseline specification in the first column. These seven factor returns explain only 12% of the total variation in return difference between Q5 and Q1 over the period and none of them has a significant coefficient. In Specification (2), we include the HML (high-minus-low) and UMD (up-minus-down) factors from the Carhart (1997) model to control for book-to-market and momentum effects. In Specification (3), we further add the Pástor and Stambaugh (2003) traded liquidity factor to control for the liquidity exposure of hedge funds. In Specifications (4) to (7), we respectively include the returns of a long-short hedge fund portfolio with respect to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Agarwal, Bakshi, and Huij (2010) risk-neutral volatility and skewness factors, the Gao, Gao, and Song (2018) RIX factor, and the Agarwal, Ruenzi, and Weigert (2017) tail risk measure.[13] In Specification (8), we add all previously discussed factors. Across different specifications, our results always indicate a significant negative alpha (or risk-adjusted return) for the Q5–Q1 portfolio that ranges from –0.49% to –0.72% per month with the t-statistic ranging from –2.93 to –4.04.

To support the argument that the relative performance difference between high and low H-Bear beta hedge funds is attributed to their differential exposure to the H-Bear factor, we present the alphas of the hedge fund quintiles (and the differential alpha) after adding the H-Bear factor into the evaluation model. In Panel A of Table 2.4, we find that controlling for the H-Bear factor alone reduces the differential alpha to –0.20 (t-statistic = –1.09). In Panel B, we also observe that the average risk-adjusted Q5–Q1 return becomes insignificant after adding the H-Bear factor as shown in Specification (9).

[13]For example, Return VOL is computed as the equal-weighted return difference between the top and bottom quintile hedge fund portfolios sorted by funds' exposures to change in risk-neutral volatility ($\beta^{\Delta VOL}$). $\beta^{\Delta VOL}$ is estimated over the past 24 months and is detailed in Appendix A1. For Return TailRisk, we compute the returns of the (5–0) portfolio sorted by TailRisk following Agarwal, Ruenzi, and Weigert (2017).

To summarize, there is a negative cross-sectional relation between H-Bear beta and expected hedge fund returns. Equivalently, hedge fund managers who choose to harvest the risk premium from selling bear risk insurance earn higher average returns than those who buy the bear risk insurance. Their significant outperformance cannot be explained by the exposure to standard risk factors documented in the hedge fund literature.

2.3.2. Fund-level analysis

The results from portfolio-level analysis demonstrate that a portfolio of hedge funds with low H-Bear beta yields significantly higher expected return than the one with high H-Bear beta. In this section, we perform Fama and MacBeth (1973) regressions that utilize the entire cross-sectional information in the data to examine whether the predictive power of H-Bear exposure for future hedge fund returns persists after simultaneously controlling for other hedge fund characteristics. In particular, each month from December 1997 to November 2017, we perform the following cross-sectional regressions:

$$r_{i,t+1} = \psi_{0,t} + \psi_t \times \beta_{i,t}^{H-BEAR} + \phi_t' \mathbf{Z}_{i,t} + \varepsilon_{i,t+1}, \tag{2.12}$$

where $r_{i,t+1}$ is the realized excess return of hedge fund i in the month $t+1$, $\beta_{i,t}^{H-BEAR}$ is the H-Bear beta of hedge fund i at the end of month t, and $\mathbf{Z}_{i,t}$ is a vector of fund characteristics. To distinguish the impact of H-Bear factor from other risk measures, we also include several hedge fund measures of risk. The details of these variables are provided in Appendix A1.

Table 2.5 reports the time-series averages of the slope coefficients, the corresponding Newey-West adjusted t-statistics (with 24 lags), and the average adjusted R^2 from 240 monthly regressions.

[Insert Table 2.5 here]

The univariate regression result in Specification (1) shows a negative relation between H-Bear beta and expected hedge fund returns. The average slope, ψ_t, from the monthly regressions of hedge fund returns on H-Bear beta is –0.59 (t-statistic = –3.63). The economic magnitude of the

H-Bear beta effect is comparable to that shown in the univariate portfolio-level analysis. Specifically, multiplying the difference in mean values of H-Bear beta between the high and low H-Bear beta quintiles from Panel A of Table 2.3 by the slope coefficient yields a monthly risk premium differential of –0.63% between the high and low H-Bear beta portfolios.

In Specification (2), we control for hedge fund characteristics, e.g., size, age, minimum investment amount, a fund's management and incentive fee, length of a fund's lockup and redemption period, as well as other measures of risk, e.g., past fund returns, fund return volatility, skewness, and kurtosis. We also add indicator variables that take the value of one in case the fund employs leverage, has a hurdle rate, has a high water mark, or is an offshore fund, and zero otherwise. In line with the prior literature, we find that minimum investment, past return, as well as past return volatility and skewness are positive and significant predictors of future hedge fund returns. More importantly, the association between H-Bear beta and future hedge fund returns remains negative (coefficient = –0.35) and statistically significant (t-statistic = –3.72).

Next, we augment the above specification by including respectively in Specifications (3) to (5) the exposure to market risk, higher risk-neutral market moments (Agarwal, Bakshi, and Huij, 2010), and market tail risk (Agarwal, Ruenzi, and Weigert, 2017), all computed based on an estimation window of 24 months. Depending on the specification, the average coefficient estimate on H-Bear beta ranges from –0.25 to –0.33 with t-statistics ranging from –3.24 to –3.33. These results indicate that the above risk measures do not subsume the predictive power of H-Bear factor exposure for future hedge fund returns.

A potential explanation for the relation between H-Bear factor exposure and future hedge fund returns is that low H-Bear beta hedge fund managers have higher level of skills. In Specification (6), we control for several measures of hedge fund skills, including the macroeconomic uncertainty timing skill (β^{UNC}) of Bali, Brown, and Caglayan (2014), the skill at exploiting rare disaster concerns (β^{RIX}) of Gao, Gao and Song (2018), the R-squared measure of Titman and Tiu (2011), the strategy distinctiveness index (SDI) of Sun, Wang, and Zheng (2012), and the downside returns of Sun, Wang, and Zheng (2018). We compute these skill measures based on a rolling window of 24 months. The average coefficient on H-Bear beta is still negative and statistically significant at the 1% level, confirming the distinctive effect of H-Bear factor exposure.

Of primary interest is Specification (7), where we control for the full set of hedge fund characteristics, exposures to other risk factors, and manager skill measures. The coefficient on H-Bear beta remains negative, –0.29, and is significant at all conventional levels with a t-statistic of –3.20.[14] Overall, our results document a strong negative cross-sectional relation between H-Bear beta and future hedge fund returns. The effect is not subsumed by hedge fund characteristics, manager skills, and fund exposures to previously documented risk factors.

2.3.3. Effect of H-Bear exposure during different market states

2.3.3.1. Market crashes versus normal times

To examine whether hedge funds with negative H-Bear betas – whose trading strategies are associated with selling insurance – are more or less exposed to market crashes, we investigate the association between H-Bear beta and hedge fund returns during market crash periods versus normal periods (defined according to the return month $t+1$). Market crashes are defined as months during which the market excess return is lower than its 10$^{\text{th}}$ percentile over the sample period.[15] We use a specification identical to that in Specification (7) of Table 2.5 to control for a large set

[14]We see that the coefficient on TailRisk changes its sign from positive (in Specification (5)) to negative (in Specification (7)) after controlling for the full set of hedge fund characteristics. At first sight, this result appears at odds with that of Agarwal, Ruenzi, and Weigert (2017). However, their sample period, 1996 to 2012, and their hedge fund sample, equity-oriented funds, are different from ours. Moreover, we have a larger set of controls. Finally, market beta has a correlation of 0.67 with TailRisk, thus containing somehow overlapping information. Via portfolio-sorting analysis, we are able to confirm a significant positive TailRisk-hedge fund return relation among equity-oriented hedge funds. Also, by using portfolio-level approach, we can verify the significant positive relations between β^{UNC} of Bali, Brown, and Caglayan (2014) or β^{RIX} of Gao, Gao and Song (2018) and future hedge fund returns during their respective sample periods. In addition, we can confirm the significant positive relations between SDI of Sun, Wang, and Zheng (2012) or downside returns of Sun, Wang, and Zheng (2018) and future hedge fund Fung-Hsieh alphas (instead of hedge fund returns) and the negative relation between the R-squared measure of Titman and Tiu (2011) and future hedge fund alphas.

[15]We obtain similar results using alternative definitions of realized market crashes, e.g., when excess market returns are lower than –10%, when excess market returns are lower than the sample period 5$^{\text{th}}$ percentile, and during the recession periods indicated by the National Bureau of Economic Research (NBER).

of fund characteristics, manager skill measures, and risk exposures. We report the coefficients on H-Bear beta and market beta but suppress the coefficients on other control variables for the sake of brevity.

[Insert Table 2.6 here]

Specification (1) of Table 2.6 shows a strong negative relation between H-Bear beta and hedge fund returns (coefficient of –1.15 and t-statistic of –2.75) during market crash periods, which is robust to controlling for market beta that captures hedge funds' unhedged market exposure. This is consistent with the idea that the H-Bear factor is negative on average even during market crashes, i.e., low H-Bear beta funds still earn the negative premium of this factor. For example, during the October 2008 crisis, the market experienced an excess return of –17.23%, but the H-Bear factor also had a negative return of –4.27%. Accordingly, low (negative) H-Bear beta funds earn an average excess return of –5.31%, while high (positive) H-Bear beta funds happen to underperform with an average excess return of –10.01%.[16] During normal times, as in Specification (2), we still observe a significant negative effect of H-Bear beta on future hedge fund returns with the coefficient on H-Bear beta equal to –0.20 (t-statistic = –1.83).

Similarly, we examine the predictive power of H-Bear factor exposure during months when the market excess returns are negative versus positive. The regression result from Specification (3) in Table 2.6 shows a negative and significant relation between H-Bear beta and hedge fund returns when the market declines. The average coefficient on H-Bear beta during these months is –0.67 (t-statistic = –2.62). When the market excess returns are positive as shown in Specification (4), we still find a negative association, but it is not statistically significant (the average H-Bear beta

[16]The evidence that both low and high H-Bear beta groups of hedge funds experience significant losses when the market crashes is understandable because both groups have positive unhedged market exposure (see again Section 2.3). This is also aligned with the notion that hedge funds on an aggregate level are exposed to substantial market downturns (see Agarwal and Naik, 2004; Jurek and Stafford, 2015). Also, using portfolio-level analysis, we find that high H-Bear beta quintile underperforms low H-Bear beta quintile by an average of 2.85% per month during the market crash periods and by an average of 1.16% per month during the negative market return periods. Results are reported in Table A2.3 of Appendix A.

coefficient = –0.06, t-statistic = –0.42). One potential explanation for the less pronounced negative H-Bear beta effect during the positive market return periods is that on some occasions, positive market returns are accompanied by persistently increase in concerns about future bear market states (for example, in periods when the market rebounds) and hence coincide with periods of positive H-Bear factor.

In contrast, in the same regressions, we find that the impact of market beta on future hedge fund returns is significantly negative in periods of market crashes or in periods of negative market returns (Specifications (1) and (3)), but strongly positive during normal times or when market returns are positive (Specifications (2) and (4)). This opposite-sign relation is expected: hedge funds with high unhedged market (or realized tail risk) exposure earn premium during normal times but perform worse when the market declines (or when tail risk materializes) (see Jiang and Kelly, 2012; Agarwal, Ruenzi, and Weigert, 2017). Therefore, the effect of H-Bear beta on hedge fund returns is distinct and far from fully explained by either the market or tail risk exposure.

Overall, our findings suggest that negative H-Bear beta funds who act as (hedged) insurance sellers do not necessarily underperform positive H-Bear beta funds who act as (hedged) insurance buyers during market crashes. This provides additional insights into the cross-sectional aspects of option-like hedge fund returns.

2.3.3.2 Positive versus negative H-Bear factor

As low H-Bear beta funds earn higher returns on average by being more exposed to bear market risk, we expect an opposite, i.e., positive, relation between H-Bear beta and hedge fund returns when bear market risk is high in month $t+1$ (i.e., when concerns about future bear market states increase). We define the periods of high (low) bear market risk as months when the H-Bear factor returns are positive (negative). We then examine the H-Bear factor exposure effect conditional on these different states and report the results in Table 2.7.

[Insert Table 2.7 here]

As expected in Specification (1) of Table 2.7, we find that the effect of H-Bear beta on future hedge fund returns is strongly negative in periods of negative H-Bear factor returns (when bear market risk is low). In particular, the average coefficient on H-Bear beta is –0.49 with a corresponding t-statistic of –3.50. However, in Specification (2) of Table 2.7, the relation reverses and becomes positive, with an average H-Bear beta coefficient of 0.44 and a t-statistic of 3.16, during periods of positive H-Bear factor returns (when bear market risk is high).[17] These results are in line with the following economic mechanism. When the H-Bear return is negative, the price of insurance does not increase enough to compensate for the negative market return or decreases more than what is expected given a positive market return. In this case, hedge funds with negative H-Bear betas (insurance sellers) outperform hedge funds with positive H-Bear betas (insurance buyers). Oppositely, when the H-Bear return is positive (i.e., there is an increase in concerns about future bear market states), the insurance return exceeds in absolute terms the negative market return or decreases less than what is expected given a positive market return. In this case, we find that funds with positive H-Bear betas outperform funds with negative H-Bear betas.

To better understand these results, recall from Panel B of Table 2.3 that the return of an insurance buyer (seller) comprises a positive unhedged position and a hedged long (short) position to the market. Also, both groups have equivalent unhedged market exposure, which is around 0.43. Hence, the relative outperformance or underperformance of each hedge fund group in different periods is purely attributed to its differential exposure to the H-Bear factor.

2.3.4. Determinants of H-Bear factor exposure

2.3.4.1. Sources of H-Bear factor exposure

In this subsection, we explore potential trading strategies that might explain the cross-sectional variation in hedge funds' exposure to the H-Bear factor. Given the construction of the H-Bear

[17]Since the periods of negative H-Bear factor are markedly more than the periods of positive H-Bear factor (189 versus 51 months, respectively), the negative relation between H-Bear beta and future hedge fund returns is the one that dominates in the overall sample period.

factor, it is obvious that a major source of the H-Bear beta might be the usage of options in combination with some exposure to the market. We illustrate this more clearly with a stylized hypothetical example that employs feasible put buying/writing strategies in the spirit of Jurek and Stafford (2015).

The example is detailed in Table A2.4 of the Appendix. In summary, Fund A follows a naked SPX put-writing strategy that requires margin, while Fund B follows a protective SPX put-buying strategy since it also allocates part of its capital to the S&P 500 index.[18] We calculate the returns of those two hypothetical funds using actual data from the period January 1996 to December 2017. Fund A significantly outperforms Fund B on average, but also during market crashes. The exposure of Fund B to realized market crashes comes from its substantial (partly hedged) investment into the market.[19] We next extract the residuals from the regression of the put-writing strategy returns on the market returns over the sample period and find that during months with negative residuals the result reverses and Fund B outperforms Fund A. Overall, our stylized scenario featuring two funds that make different use of SPX put options and are differentially exposed to the market provides a pattern that is very similar to what we find in our main analysis using hedge funds sorted by their exposure to the H-Bear factor.

To show more explicitly how simple put buying/writing strategies can give rise to differential exposure to the H-Bear factor, we perform a Fama and MacBeth (1973) regression analysis of the H-Bear beta of fund i in month t on the contemporaneous hedge fund exposure to such strategies:

$$\beta_{i,t}^{H-BEAR} = \alpha_t + \lambda_t' \boldsymbol{\beta}_{\boldsymbol{i,t}}^{\boldsymbol{Strategy}} + \phi_t' \boldsymbol{\beta}_{\boldsymbol{i,t}}^{\boldsymbol{X}} + \varepsilon_{i,t}, \tag{2.13}$$

[18]Details about the design of those strategies and the estimation of their returns are provided in Table IA.4 of the Internet Appendix. The inference that we draw is robust to different levels of leverage employed or different option strike prices.

[19]In this respect, Fund B does not simply earn the negative of the Fund A returns and vice versa. In an unreported analysis, the regression of put-buying strategy (Fund B) returns on put-writing strategy (Fund A) returns, which itself proxy for downside market risk according to Jurek and Stafford (2015), yields a significant negative alpha (constant). This implies that downside market risk cannot explain the relative performance of put buyers and sellers in our context.

where $\beta_{i,t}^{H-BEAR}$ is the H-Bear beta of hedge fund i in month t, $\boldsymbol{\beta}_{i,t}^{\boldsymbol{Strategy}}$ is a vector of fund i's exposures to a series of trading strategies in month t estimated using a rolling window of 24 months, and $\boldsymbol{\beta}_{i,t}^{\boldsymbol{X}}$ is a vector of exposures to other risk factors. Specification (1) of Table 2.8 presents the results. As expected, we find a highly significant negative relation between H-Bear beta and $\beta^{Put-Writing}$ (coefficient of –0.84 and t-statistic = –8.33) and a highly significant positive relation between H-Bear beta and $\beta^{Put-Buying}$ (coefficient of 2.96 and t-statistic = 9.63). This result confirms that a high (low) H-Bear beta might be driven by protective put-buying (naked put-writing) strategies. Note, however, that a series of popular hedge fund trading strategies such as merger arbitrage, yield curve arbitrage, convertible arbitrage etc., exhibit returns that resemble the writing of put options (Agarwal and Naik, 2004). Distinguishing the effect of such strategies on the H-Bear beta from the respective effect of put option writing is inherently difficult. Therefore, we acknowledge that, even though the usage of options appears to be a driving force of the H-Bear beta, standard hedge fund arbitrage strategies might also contribute to a large extent especially in the case of the low H-Bear beta values.

As a next step, we hypothesize that hedge funds exhibit cross-sectional variation in their exposure to the H-Bear factor because they possess stocks which are themselves differentially exposed to the H-Bear factor. Lu and Murray (2019) show that low bear beta stocks yield significantly higher expected returns than otherwise similar stocks. We use the low minus high bear beta stock factor (Stock-Bear factor) as a proxy for bear market risk induced by equity holdings. The Stock-Bear factor is constructed as the return of a trading strategy that goes long stocks with high bear market risk exposure (i.e., stocks in the bottom quintile of bear beta) and goes short in stocks with low bear market risk exposure (i.e., stocks in the top quintile of bear beta).[20] In Specification (2) of Table 2.8, we regress H-Bear beta on funds' exposure to the Stock-Bear factor ($\beta^{Stock-Bear}$). The average slope coefficient of $\beta^{Stock-Bear}$ is negative (at –0.25) and statistically significant at

[20]Lu and Murray (2019) estimate the bear beta for each individual stock using overlapping returns for five-day periods ending in months $t-11$ through t.

the 1% level (t-statistic = –2.80). This confirms that low H-Bear beta hedge funds are likely buyers of low bear beta stocks, whilst high H-Bear beta hedge funds are likely buyers of high bear beta stocks.

Finally, in Specification (3) of Table 2.8, we control for a list of hedge fund return exposures including funds' exposures to the Fung and Hsieh (2004) trend-following factors, the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Gao, Gao, and Song (2018) RIX factor, and the Agarwal, Ruenzi, and Weigert (2017) tail risk. Our results remain unchanged: H-Bear beta appears to be driven by a fund's sensitivity to the Stock-Bear trading, naked put-writing, and protective put-buying strategies.

2.3.4.2 H-Bear factor exposure and hedge fund characteristics

To further understand which funds are more or less likely to be exposed to bear market risk, we next examine which fund characteristics and other risk measures are associated with H-Bear beta. We perform a series of Fama and MacBeth (1973) regressions of the H-Bear beta of hedge fund i in month t on various contemporaneous characteristics and risk measures of fund i:

$$\beta_{i,t}^{H-BEAR} = \alpha_t + \phi_t' \mathbf{Z}_{i,t} + \varepsilon_{i,t}, \tag{2.14}$$

where $\beta_{i,t}^{H-BEAR}$ is the H-Bear beta of hedge fund i in the month t, and $\mathbf{Z}_{i,t}$ is a vector of fund characteristics. Table 2.9 reports the time-series averages of the slope coefficients and the corresponding Newey-West adjusted t-statistics (with 24 lags).

[Insert Table 2.9 here]

Specification (1) of Table 2.9 investigates the association between H-Bear beta and time-varying fund characteristics such as fund size, age, return volatility, skewness, kurtosis and past yearly return. We find that hedge funds with low H-Bear betas tend to be younger. Intuitively, young funds probably have incentives to attract fund flows by establishing a track record of high returns early in their life cycle. Thus, these funds are more likely to get involved in trading strategies that resemble selling market insurance since it offers high compensation. Furthermore, consistent with risk-inducing behavior, there is a positive relation between H-Bear beta of hedge funds and their return skewness. Equivalently, low H-Bear beta funds, which are more exposed to bear market risk, exhibit left-skewed return distributions. However, despite having more negative return skewness, these funds have higher past-year returns.

In Specification (2), we include time-invariant contractual features such as a fund's minimum investment amount, management and incentive fees, lockup and redemption periods, as well as indicator variables that equal one if a given fund is offshore, employs leverage, has a high-water mark and a hurdle rate. Intuitively, hedge funds with low H-Bear betas are associated with measures of managerial incentives such as high management fees, existence of a hurdle rate, and offshore location. There is a positive relation between fund H-Bear beta and incentive fee, but this finding is consistent with Agarwal, Daniel, and Naik (2009) who find that incentive fees do not capture managerial incentives as two managers charging the same incentive fee can face different dollar incentives. We find a mixed relation between H-Bear beta and managerial discretion. Specifically, funds with low H-Bear betas have longer redemption periods and are probably more flexible in taking on riskier positions, but are less likely to employ leverage. Intuitively, hedge funds that employ leverage tend to act more as Bear buyers, probably because their trading profile is already quite risky. In contrast, unlevered hedge funds tend to act more as Bear sellers probably because they find alternative ways to boost their returns rather than employing leverage.

In Specification (3), we include all fund characteristics and contractual features together in the same regression model. Although, the statistical significance of some of the variables is reduced, the main findings about the determinants of H-Bear beta remain intact.

2.4. Further analysis

2.4.1. H-Bear exposure and long-term future hedge fund returns

We further investigate how strong the exposure to H-Bear factor is in terms of predicting long-term future hedge fund returns. From a practical point of view, this is important because some investors and hedge fund managers might be more interested in long-term investment horizons. Indeed, lockup periods for hedge fund managers can be sometimes up to one year.

[Insert Table 2.10 here]

First, we examine the returns of H-Bear beta-sorted portfolios by holding them for long-term horizons ranging from 3 months to 24 months. We follow Jegadeesh and Titman (1993) and implement the independently managed portfolio strategy to address the returns from overlapping holding periods. Panel A of Table 2.10 reveals a significant performance persistence for up to 24 months ahead, with return spreads between high and low H-Bear beta funds of –0.58%, –0.49%, –0.30%, and –0.18% per month for a holding horizon of three, six, twelve, and twenty-four months, respectively. Moreover, these return differences are statistically significant at the 5% level, showing that H-Bear beta can successfully predict long-horizon cumulative hedge fund returns for up to 24 months into the future.

Fund returns are often reported with a lag and it takes some time to start an investment into a hedge fund. Considering this practical issue in investing in hedge funds, we implement a portfolio strategy that is identical to that in Panel A except that we now leave a one-month gap between the portfolio formation month and the month in which portfolio returns start being calculated. The results reported in Panel B of Table 2.10 are similar to those presented in Panel B. In particular, we still observe a significant outperformance of low H-Bear beta hedge funds compared to high H-Bear beta hedge funds even when considering an 18-month holding period.

2.4.2. H-Bear exposure conditional on investment styles

To provide some insights as to whether the predictive power of H-Bear factor for future hedge fund returns is an inter- versus intra-style effect, we examine the performance (returns and alphas) of portfolios sorted based on their H-Bear factor exposures separately using funds within each investment style. Table 2.11 presents the results.

[Insert Table 2.11 here]

We exclude the short-bias category because, as shown in Table 2.1, we do not have enough observations to perform a meaningful analysis. Table 2.11 shows that there is a high variation in H-Bear betas within each hedge fund investment style. Consistent with this finding, we further observe a strong and negative relation between H-Bear beta and portfolio returns in all the nine investment styles. Among the most significant styles, return spreads between the high and low H-Bear beta quintiles are –0.72% per month for relative value, –0.70% for global macro, and –0.61% for multi-strategy. The corresponding alpha differentials are also economically substantial and statistically significant. The return and associated alpha spreads are lower among equity market-neutral, fund of funds, and long-short equity funds, but they are all statistically significant. In summary, there is a high variation in the H-Bear beta within each investment style and hedge funds seem to exhibit both inter- and intra-style bear market risk pricing.

2.4.3. H-Bear factor exposure versus manager skills at exploiting rare disaster concerns

In a related study, Gao, Gao, and Song (2018) also use a positioning in put options (see their Equation (4)) in order to capture investors' perceptions about market-wide tail risk and show that hedge funds with high sensitivity to a rare disaster concern index (RIX) earn on average higher returns than hedge funds with low sensitivity to the RIX index. Their put portfolio is more complicated and is designed to capture extreme negative price movements. In contrast, our Bear portfolio is simpler, and the level of extreme returns captured can be easily adjusted. Despite this difference, the two put option portfolios are conceptually similar. Therefore, it is important to understand why the results of our study are different from theirs.

Gao, Gao, and Song's (2018) RIX index is the *average daily price within a month* of a portfolio of put options on various indices from sectors including banking, semiconductor, precious metals, housing, oil service, and utilities. Hedge funds' sensitivity to this measure (β^{RIX}) is interpreted as skill in exploiting the market's ex-ante rare disaster concerns.[21] In contrast, the Bear factor is the *monthly return* of a portfolio of put options (accordingly, the H-Bear factor can be interpreted as the return of a market-hedged put option portfolio). As a result, it captures the return of an insurance contract against concerns about future bear market states. Our conjecture is that the difference in the results of the two studies comes from the different approaches in using average prices within the month versus monthly returns and not from the different portfolio of puts that is used in each study. This implies that if we use the return – rather than the price level – of the same portfolio of put options that form the RIX index, we will get a predictive pattern that resembles the one presented in this study.

[Insert Table 2.12 here]

Panel A of Table 2.12 presents the results from a portfolio sorting exercise based on hedge fund sensitivities to various versions of the RIX index estimated controlling for the market excess returns. For consistency with Gao, Gao and Song's (2018) study, all the results span the period from January 1998 to December 2011 and are based on decile portfolios. Specification (1) uses the RIX index that is made publicly available by George Gao and covers the period 1996–2011. We observe a pattern that is very close to what is reported in Gao, Gao and Song (2018). Specification (2) presents the result of the same analysis but with our replication of the RIX index. Our RIX index has a 99% correlation with the RIX index provided by Gao and hence, as expected, the results are very close to Specification (1). Specification (3) shows the results using a RIX index constructed using only S&P 500 index options – rather than using a mixture of six indices as in the main RIX. Similar to Gao, Gao, and Song (2018) (see their Internet Appendix), we find a positive albeit less significant association between the sensitivity to this RIX index and hedge fund returns. Overall, high RIX beta funds, on average, outperform low RIX beta funds and they are able to avoid

[21]Gao, Gao and Song's (2018) finding does not point to a risk-based explanation. RIX is persistent with an auto-correlation coefficient of 0.92, which is not a risk factor per se as the innovations in concerns about future bear market states.

significant losses when market crashes occur. According to Gao, Gao, and Song (2018), this is because these high RIX beta funds skilfully time the selling of overpriced crash insurance.

Specification (4) in Panel A of Table 2.12 shows the main result of this section. We construct an investable disaster concern factor from a portfolio of S&P 500 put options as in Equation (4) in Gao, Gao, and Song (2018). The factor captures the return of the put option portfolio, rather than the average daily price within the month. The option positions are formed on a daily basis, and the daily returns within the month are averaged to create the monthly RETRIX. The construction of this investable factor is detailed in Appendix A1. We argue that the covariance between hedge fund returns and the returns, rather than the contemporaneous price levels, of a portfolio of put options provides an intuitive way to classify hedge funds as insurance buyers or sellers. Now, we observe that the pattern is reversed and there is a negative and significant association between sensitivity to RETRIX (β^{RETRIX}) and future hedge fund returns. Furthermore, in line with our main empirical evidence, insurance sellers still outperform insurance buyers during periods of market crashes. However, this is not because these insurance sellers have higher skills, but because they are mechanically more exposed to bear market (or disaster) risk.

It is reasonable to ask whether β^{RETRIX} absorbs the positive effect of β^{RIX} on future hedge fund returns. To answer this question, we report in Panel B of Table 2.12 two sets of bivariate dependent sorts according to β^{RETRIX} and β^{RIX}. In Panel B.1, we first sort all hedge funds into quintiles based on their RETRIX betas, and then within each RETRIX beta quintile, we further sort funds into five portfolios based on their RIX betas. We observe the outperformance of high RIX beta funds relative to low RIX beta funds in all RETRIX beta quintiles. Possibly, RIX beta reflects a skillful timing of selling crash insurance rather than a blind selling of it, thus containing a different information from the exposure to bear market risk. In Panel B.2, when we first sort hedge funds based on RIX betas into quintiles and then sorts funds within each RIX beta quintile into five RETRIX beta portfolios, we still observe the outperformance of low RETRIX beta funds relative to high RETRIX beta funds within each RIX beta quintile. The risk-adjusted return spreads of high-minus-low RETRIX beta portfolios range from –0.33% to –0.83% per month, all statistically significant at the 5% level.

Overall, the results of this section show that the exact portfolio of put options that is used to capture negative market movements is of secondary importance for analyzing the cross-section of hedge fund returns. What is of primary importance is whether we consider the average price of this portfolio (the sensitivity to which reflects skill according to Gao, Gao, and Song (2018)) or the return of this portfolio (the sensitivity to which reveals whether a hedge fund acts more as an insurance buyer or seller).

2.5. Robustness checks

In this section, we further corroborate our findings in this chapter by conducting a battery of robustness checks on the predictive power of H-Bear beta for one-month ahead hedge fund returns based on portfolio-level analyses.

[Insert Table 2.13 here]

First, instead of examining equal-weighted returns as in our baseline analysis, we use value-weighted returns. Specification (1) of Table 2.13 shows that the H-Bear factor effect is both statistically and economically significant when portfolio returns are weighted by AUM. For example, the underperformance of hedge funds in the highest H-Bear beta, compared to the lowest H-Bear beta, quintile is economically large, generating an average return spread of –0.63% per month with a t-statistic of –3.42. The associated alpha difference between these two quintiles is –0.73% per month and also statistically significant.

Second, we examine the stability of our results by changing the H-Bear beta estimation horizon from 24 months to either 12 or 36 months. As shown in Specifications (2) and (3) of Table 2.13, the Q5–Q1 portfolio return spreads are –0.50% and –0.42% per month for a H-Bear beta estimation horizon of 12 months and 36 months, respectively. The corresponding t-statistics are –2.75 and –4.30. The risk-adjusted returns of the Q5–Q1 H-Bear beta portfolio based on the Fung and Hsieh

(2004) seven factor model are also negative and statistically significant at the 1% level in both specifications.

Third, we investigate whether our results are robust to alternative definitions of the Bear portfolio. In Specifications (4) and (5) of Table 2.13, we define bear region as states in which the market excess return is one or two standard deviations, instead of 1.5 standard deviations, below zero. We still find significantly negative return and Fung-Hsieh alpha differences between the portfolio of high $\beta_{1\sigma}^{H-BEAR}$ (or $\beta_{2\sigma}^{H-BEAR}$) hedge funds and the portfolio of low $\beta_{1\sigma}^{H-BEAR}$ (or $\beta_{2\sigma}^{H-BEAR}$) hedge funds. Next, we use only the long put position by dropping the short put position from the Bear portfolio. This put portfolio is simpler and conceptually closer to the portfolio utilized by Agarwal and Naik (2004). As shown in Specification (6) of Table 2.13, the portfolio of low β^{H-PUT} hedge funds outperforms the portfolio of high β^{H-PUT} hedge funds with significant return and alpha differences. In an unreported analysis, we also find that hedge funds with low β^{H-PUT} still outperform hedge funds with high β^{H-PUT} during periods of market crashes.

Fourth, prior studies document substantial serial correlation of hedge fund returns due to illiquidity exposure and return smoothing of funds (Getmansky, Lo, and Makarov, 2004). If this is the case, hedge fund returns would appear less volatile. To remove the effect of serial correlation, we apply the correction method of Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns. We then re-estimate H-Bear beta and run our tests using the unsmoothed fund returns in Specification (7) of Table 2.13. We still observe significant return and respective Fung-Hsieh alpha spreads between high and low H-Bear beta hedge fund portfolios. Furthermore, in Table A2.5, we show that the effect of H-Bear beta on future fund returns remains robust to controlling for several lags in hedge fund returns.

Fifth, as a way to mitigate survivorship bias, in Specification (8) of Table 2.13 we repeat the baseline analysis by assuming that returns of the drop-out funds are –100% in the month following the last reporting month. This is because the HFR database does not report delisting hedge fund returns. This delisting return assumption does not change our conclusion. For instance, the return and alpha spreads between Q5 and Q1 are –0.80% (t-statistic = –4.41) and –0.93% (t-statistic = –

4.46), respectively. Besides, our results are not materially affected when we assign different values for delisted hedge fund returns, such as –75%, –50%, –25%, and zero.

Sixth, in Specification (9) of Table 2.13, we examine the performance of hedge fund portfolios sorted by H-Bear beta using the Goetzmann, Ingersoll, Spiegel, and Welch (2007)'s manipulation-proof performance measure (MPPM) with the rho coefficient equal to three. We find that low H-Bear beta funds have an average MPPM of 0.020 while high H-Bear beta funds have an average MPPM of –0.014. The associated MPPM difference is –0.034 with a t-statistic of –3.65.

Finally, to address the concern that our empirical findings only apply to the HFR database, we attempt to verify our main results using the Lipper TASS and the EurekaHedge databases. Results including portfolio-level and fund-level analyses using these two different databases are reported in Table A2.6 and Table A2.7 of the Appendix. Overall, our inference regarding the predictive power of H-Bear factor exposure remains unchanged. For example, when we consider the Lipper TASS database, high H-Bear beta funds on average underperform low H-Bear beta funds by –0.42% per month (t-statistic = –3.55). The Fung-Hsieh 7-factor alpha difference between these two quintiles is –0.53% per month (t-statistic = –4.07). Furthermore, the average coefficient on H-Bear beta remains negative (at –0.21 and t-statistic = –2.99) in the multivariate regression controlling for the full set of hedge fund characteristics, exposures to other risk factors, and manager skill measures.

2.6. Conclusion

In this chapter, we document that the exposure of hedge funds to the market-hedged Bear factor can explain a large proportion of the cross-sectional variation in their returns. We show that, despite a strong negative relation, the market and the Bear portfolio do not move in lockstep. Thus, the relative price movement between the two, captured by the return of the H-Bear factor, is a proxy for the innovation in ex-ante concerns about future bear market on top of what is justified by the concurrent market return.

In a portfolio-level analysis, hedge funds in the lowest H-Bear beta quintile (bear risk insurance sellers) outperform hedge funds in the highest H-Bear beta quintile (bear risk insurance buyers) by 0.58% per month an average. The risk-adjusted return difference between these two hedge fund quintiles remains economically large and statistically significant. Results from multivariate regressions reveal a negative and statistically significant effect of H-Bear beta on future hedge fund returns after controlling for a large set of fund characteristics and risk attributes. Therefore, the explanatory power of the H-Bear factor exposure is distinct from previously documented hedge fund return predictors.

Our interpretation for the above findings is that low H-Bear beta funds earn higher returns on average by harvesting the bear market risk premium, while high H-Bear beta funds earn lower returns on average because they willingly pay this premium. Consistent with our risk-based explanation, the relation between H-Bear beta and future fund returns is reversed and becomes positive during months when bear market risk is high (i.e., positive H-Bear returns). In contrast, the association remains negative in the rest of the periods, and even in periods of negative market returns or during market crashes. Overall, our evidence shows that in the cross-section, low H-Bear beta hedge funds who act as insurance sellers outperform high H-Bear beta hedge funds who act as insurance buyers by being more exposed to bear market risk, but without necessarily being more exposed to market tail (crash) risk.

Figure 2.1: Time-series of market hedged Bear factor

The figure plots the monthly time-series of the market-hedged Bear portfolio (i.e., H-Bear) returns over January 1998 to December 2017. H-Bear return in month t is equal to the intercept coefficient plus the month t residual from a regression of the Bear portfolio excess returns on the market excess returns over the past 24 months. Bear portfolio excess return (Bear factor) is the one-month buy-and-hold excess return of a bear spread portfolio that longs an OTM put and shorts a further OTM put on the S&P 500 index.

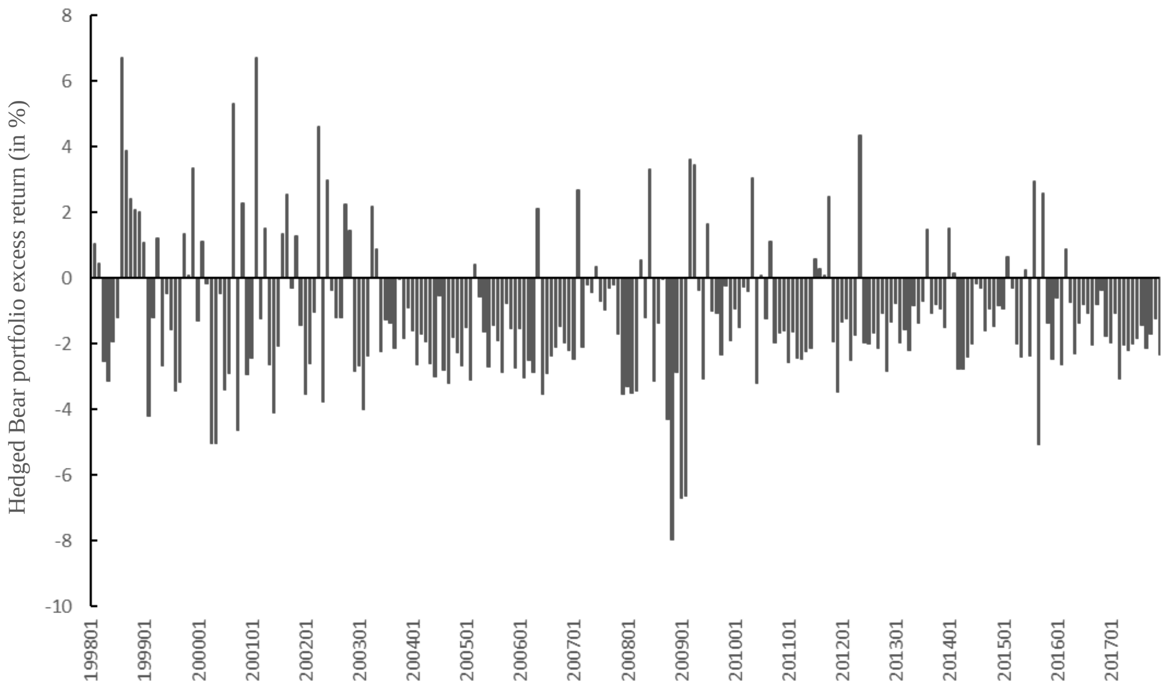

Table 2.1: Descriptive statistics of hedge funds

The table presents summary statistics for the hedge funds used in our sample. Panel A shows the time-series average of the monthly cross-sectional mean, standard deviation, and percentiles for the returns (in percent) of hedge funds in each investment style category and in total. N is the number of distinct hedge funds in each category. Panel B presents cross-sectional mean and distribution statistics for hedge fund characteristics including size, age, management fee, incentive fee, redemption notice period, lockup period, and minimum investment amount for all hedge funds in our sample. Our sample covers hedge funds from the HFR database over the period from January 1996 to December 2017.

Panel A: Summary statistics of hedge fund returns (in percent) by categories

	N	Mean	STD	P10	P25	P50	P75	P90
Event-Driven	832	0.70	3.22	–1.86	–0.48	0.61	1.74	3.27
Relative Value	1366	0.62	2.74	–1.54	–0.26	0.64	1.56	2.84
Long-Short Equity	2936	0.78	4.73	–3.93	–1.46	0.70	2.91	5.51
Global Macro	443	0.64	4.39	–3.71	–1.31	0.54	2.47	5.08
CTA	422	0.45	4.20	–3.67	–1.30	0.33	2.05	4.64
Equity Market-Neutral	549	0.42	2.30	–2.08	–0.76	0.42	1.57	2.95
Multi-Strategy	1715	0.65	4.07	–3.32	–1.17	0.58	2.37	4.63
Short-Bias	60	–0.15	3.55	–4.50	–2.45	–0.19	2.11	4.30
Sector	505	0.97	5.20	–4.56	–1.74	0.90	3.48	6.56
Fund of Funds	2256	0.50	1.86	–1.17	–0.26	0.50	1.26	2.14
All hedge funds	11084	0.64	4.03	–2.93	–0.83	0.55	2.01	4.24

Panel B: Summary statistics of hedge fund characteristics

	N	Mean	STD	P10	P25	P50	P75	P90
Average monthly AUM ($M)	11084	175.22	604.65	14.20	23.59	52.31	140.33	370.31
Average age (in months)	11084	78.33	63.95	16.27	31.96	60.00	107.01	167.07
Management fee (%)	11084	1.44	0.57	1.00	1.00	1.50	2.00	2.00
Incentive fee (%)	11084	15.78	7.54	0.00	10.00	20.00	20.00	20.00
Redemption (in months)	11084	1.24	1.10	0.03	0.33	1.00	2.00	3.00
Lock Up (in months)	11084	3.46	6.92	0.00	0.00	0.00	6.00	12.00
Minimum Investment ($M)	11084	1.26	4.63	0.05	0.10	0.50	1.00	2.00

Table 2.2: Descriptive statistics for Bear portfolio and analysis of its returns

The table reports summary statistics and factor analysis for the Bear factor. Bear factor is the one-month buy-and-hold excess return of a bear spread portfolio that longs an OTM put and shorts a further OTM put on the S&P 500 index. Panel A presents the mean (Mean), standard deviation (STD), skewness (Skew), minimum value (Min), 10th percentile value (P10), 50th percentile value (P50), 90th percentile value (P90), and maximum value (Max) for the monthly time-series of the Bear factor (Bear) and the market factor (MKT) from January 1996 to December 2017. Panel B shows the result from the time-series regression of the Bear factor on the market factor over 264 months from January 1996 to December 2017. Panel C reports the summary statistics for the market-hedged Bear factor return (H-Bear) over January 1998 to December 2017, where H-Bear return in month t is equal to the intercept coefficient plus the month t residual from a regression of the Bear portfolio excess returns on the market excess returns over the past 24 months. Panel D shows the association between H-Bear and MKT in different market states. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Summary statistics of the Bear portfolio excess returns (in percent)

Factor	Mean	STD	Skew	Min	P10	P50	P90	Max
Bear	–1.64	4.41	2.64	–5.18	–4.71	–3.27	4.10	27.55
MKT	0.65	4.41	–0.72	–17.23	–5.46	1.19	6.08	11.35

Panel B: Analysis of the Bear portfolio excess returns

	(1)	(2)
Constant	–1.64***	–1.09***
	(–5.04)	(–6.77)
MKT		–0.85***
		(–15.90)
Adjusted R^2	0.00	0.72

Panel C: Summary statistics of the H-Bear return (in percent; based on 24-month rolling window)

Factor	Mean	STD	Skew	Min	P10	P50	P90	Max
H-Bear	–1.25	2.30	0.97	–8.72	–3.35	–1.69	2.02	9.20

Panel D: Relation between H-Bear factor return and market return in different market states

	Average H-Bear	Average MKT
MKT < 0	–1.41	
MKT > 0	–1.16	
5 largest market losses	–0.22	
H-Bear < 0		0.24
H-Bear > 0		1.69

Table 2.3: H-Bear beta quintile portfolios and market exposure

The table reports the average H-Bear beta and market exposure based on different regression models for each H-Bear beta quintile portfolio. H-Bear beta (β^{H-BEAR}) is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles according to their H-Bear betas. Quintile 1 (5) consists of funds with the lowest (highest) H-Bear betas. For each quintile, we report the time-series average of regression coefficients. In Panel A, β^{M} and β^{H-BEAR} are respectively the coefficients $\beta_{i,t}^{M}$ and $\beta_{i,t}^{H-BEAR}$ from the regression of monthly hedge fund excess returns on the market excess returns and the plain Bear factor returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$ over the past 24 months. In Panel B, β^{MKT} and β^{H-BEAR} are respectively the coefficients $\beta_{i,t}^{MKT}$ and $\beta_{i,t}^{H-BEAR}$ from the regression of monthly hedge fund excess returns on the market excess returns and the market-hedged Bear factor returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{H-BEAR,t} + \epsilon_{i,t}$ over the past 24 months, where the market-hedged Bear factor returns are estimated as residuals from the regression of the plain Bear factor returns on the market excess returns over the past 24 months. Note that despite the different regression models in Panels A and B, the β^{H-BEAR} coefficients are identical, hence the same notation. In Panel C, β^{BEAR} is the coefficient $\beta_{i,t}^{BEAR}$ from the regression of monthly hedge fund excess returns on the plain Bear factor returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$ over the past 24 months. We also report the results for the Q5–Q1. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Regression model with market factor and plain Bear factor (coefficient for the latter becomes $\beta_{i,t}^{H-BEAR}$ because we control for the market): $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$

Sort by β^{H-BEAR}	Q1	Q2	Q3	Q4	Q5	Q5–Q1	t-stat (Q5–Q1)
β^{M}	–0.04	0.15	0.22	0.36	0.89	0.93***	(10.54)
β^{H-BEAR}	–0.55	–0.14	–0.03	0.10	0.53	1.08***	(13.55)

Panel B: Regression model with market factor and market-hedged Bear factor (coefficient $\beta_{i,t}^{H-BEAR}$ is by construction identical to Panel A): $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{H-BEAR,t} + \epsilon_{i,t}$

Sort by β^{H-BEAR}	Q1	Q2	Q3	Q4	Q5	Q5–Q1	t-stat (Q5–Q1)
β^{MKT}	0.43	0.27	0.24	0.28	0.43	0.01	(0.10)
β^{H-BEAR}	–0.55	–0.14	–0.03	0.10	0.53	1.08***	(13.55)

Panel C: Regression model with plain Bear factor: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$

Sort by β^{H-BEAR}	Q1	Q2	Q3	Q4	Q5	Q5–Q1	t-stat (Q5–Q1)
β^{BEAR}	–0.51	–0.28	–0.22	–0.22	–0.27	0.24***	(4.63)

Table 2.4: Performance of H-Bear beta-sorted hedge fund portfolios

The table reports the results from the analysis of H-Bear beta-sorted hedge fund portfolios. H-Bear beta (β^{H-BEAR}) is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. Panel A presents the average returns and Fung-Hsieh alphas (in monthly percentages) of hedge fund portfolios sorted with respect to H-Bear beta. At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles according to their H-Bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) H-Bear betas. We hold these quintile portfolios for one month and present the average equal-weighted returns and alphas for each quintile and for the Q5–Q1 portfolio. Panel B presents alphas (or intercept coefficients) and slope coefficients from time-series regressions of the monthly equal-weighted Q5–Q1 H-Bear beta portfolio returns on different risk factors. As standard risk factors, we use the seven factors from the Fung and Hsieh (2004) model, which include three trend-following risk factors (PTFSBD, PTFSFX, PTFSCOM), two equity-oriented risk factors (S&P, SCMLC), and two bond-oriented risk factors (BD10RET, BAAMTSY). In addition to the Fung and Hsieh (2004) seven factors, we use the Fama and French (1993) value factor (HML), the Carhart (1997) momentum factor (UMD), the Pastor and Stambaugh (2003) liquidity factor (PS LIQ), and returns of a long-short hedge fund portfolio with regard to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor (Return Macro), the Agarwal, Bakshi, and Huij (2010) relative change in risk-neutral volatility and skewness (Return VOL and Return SKEW), the Gao, Gao, and Song (2018) RIX factor (Return RIX), and the Agarwal, Ruenzi, and Weigert (2017) tail risk factor (Return TailRisk). We also present in Panel A and B the alphas of the hedge fund quintiles (and the differential alpha) after adding the H-Bear factor return (the intercept coefficient plus the month t residual from a regression of the Bear portfolio excess returns on the market excess returns over the past 24 months). Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Univariate portfolio sorts

	Q1	Q2	Q3	Q4	Q5	Q5–Q1
Equal-weighted returns (%)	0.87	0.56	0.47	0.44	0.29	–0.58***
	(5.44)	(5.00)	(3.93)	(3.27)	(1.61)	(–3.53)
FH alpha	0.70	0.40	0.30	0.23	–0.02	–0.72***
	(4.04)	(3.94)	(3.21)	(2.38)	(–0.17)	(–3.73)
H-Bear alpha	0.70	0.44	0.43	0.51	0.49	–0.20
	(4.49)	(4.18)	(3.61)	(4.07)	(2.52)	(–1.09)
FH + H-Bear alpha	0.35	0.20	0.19	0.17	–0.01	–0.36*
	(1.63)	(1.77)	(1.81)	(1.67)	(–0.06)	(–1.73)

Panel B: Alphas after controlling additional factors

	(1) Q5–Q1	(2) Q5–Q1	(3) Q5–Q1	(4) Q5–Q1	(5) Q5–Q1	(6) Q5–Q1	(7) Q5–Q1	(8) Q5–Q1	(9) Q5–Q1
Alpha	–0.72***	–0.69***	–0.67***	–0.59***	–0.57***	–0.61***	–0.71***	–0.49***	–0.27
	(–3.73)	(–3.34)	(–2.93)	(–4.04)	(–3.63)	(–3.12)	(–3.57)	(–3.38)	(–1.49)
PTFSBD	–0.02	–0.02	–0.02	–0.03	–0.03	–0.02	–0.02	–0.03*	–0.03*
	(–1.00)	(–1.20)	(–1.24)	(–1.62)	(–1.64)	(–1.03)	(–1.37)	(–1.85)	(–1.87)
PTFSFX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(–0.29)	(–0.08)	(–0.05)	(–0.16)	(–0.19)	(0.11)	(–0.24)	(–0.20)	(–0.36)
PTFSCOM	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00
	(1.15)	(1.00)	(1.01)	(0.90)	(0.34)	(1.10)	(0.53)	(0.05)	(0.07)
S&P	0.13	0.11	0.11	0.11	0.08	0.09	0.27	0.19	0.18
	(1.51)	(1.41)	(1.34)	(1.53)	(1.48)	(1.01)	(1.52)	(1.51)	(1.50)
SCMLC	0.12	0.12*	0.12**	0.14**	0.03	0.13**	0.18*	0.10**	0.09**
	(1.55)	(1.94)	(2.00)	(2.12)	(0.84)	(2.28)	(1.86)	(2.14)	(1.98)
BD10RET	0.00	0.00	0.00	0.01*	0.00	0.01	0.00	0.00	0.00
	(0.70)	(0.83)	(0.82)	(1.68)	(–0.08)	(1.27)	(0.68)	(0.52)	(0.19)
BAAMTSY	0.00	0.00	0.01	0.01	0.00	0.01*	–0.01	0.00	0.00
	(0.40)	(0.43)	(0.52)	(0.88)	(–0.16)	(1.87)	(–0.80)	(–0.26)	(–0.58)
HML		–0.16***	–0.16***	–0.14**	–0.05*	–0.16***	–0.25**	–0.11**	–0.11**
		(–3.20)	(–3.32)	(–2.46)	(–1.62)	(–2.85)	(–2.23)	(–2.09)	(–2.13)
UMD		–0.01	–0.01	0.01	–0.02	–0.01	–0.03	–0.03	–0.03
		(–0.25)	(–0.30)	(0.17)	(–0.51)	(–0.28)	(–0.74)	(–0.73)	(–0.74)
PS LIQ			0.01					(0.00	0.00
			(0.40)					(–0.08)	(0.10)
Return Macro				–0.19***				–0.09	–0.09
				(–2.91)				(–1.33)	(–1.37)
Return VOL					0.50***			0.44***	0.47***
					(3.16)			(2.90)	(3.03)
Return SKEW					0.31***			0.27**	0.25**
					(3.25)			(2.38)	(2.35)
Return RIX						–0.23		–0.17	–0.15
						(–1.47)		(–1.15)	(–1.04)
Return TailRisk							–0.26	–0.20*	–0.20*
							(–1.22)	(–1.87)	(–1.94)
H-Bear factor									0.11***
									(2.64)
Adjusted R^2	0.12	0.17	0.17	0.25	0.41	0.20	0.22	0.47	0.47
Observations	240	240	240	240	240	240	240	240	240

Table 2.5: Fama and MacBeth regressions

The table presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund excess returns in month $t+1$ on H-Bear beta (β^{H-BEAR}) and other control variables measured at the end of month t over the sample period from January 1998 to December 2017. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. The control variables include different fund characteristics, manager skill measure, and other measures of risks. A detailed definition of these variables is provided in Appendix A1. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.53***	0.20	0.18*	0.19	0.20*	0.10	0.17
	(4.42)	(1.64)	(1.68)	(1.61)	(1.78)	(0.72)	(1.63)
β^{H-BEAR}	–0.59***	–0.35***	–0.25***	–0.29***	–0.33***	–0.22***	–0.29***
	(–3.63)	(–3.72)	(–3.24)	(–3.30)	(–3.33)	(–3.79)	(–3.20)
Size		–0.02	–0.01	–0.02	–0.01	–0.01	0.00
		(–1.23)	(–1.01)	(–1.21)	(–1.08)	(–0.86)	(–0.44)
Age		–0.07	–0.06	–0.10	0.12	–0.10	0.12
		(–0.20)	(–0.18)	(–0.33)	(0.38)	(–0.42)	(0.61)
Min Investment		1.23***	1.13***	1.23***	1.10***	1.02**	0.76**
		(2.82)	(2.69)	(2.88)	(2.89)	(2.46)	(2.16)
Management Fee		–1.77	–0.82	–2.14	–1.19	–1.76	–0.46
		(–0.70)	(–0.39)	(–0.91)	(–0.42)	(–0.88)	(–0.27)
Incentive Fee		0.19	0.17	0.22*	0.21*	0.17	0.22
		(1.41)	(1.35)	(1.65)	(1.70)	(1.26)	(1.63)
Lock Up		0.19	0.06	0.23	0.09	0.14	0.01
		(0.75)	(0.32)	(0.95)	(0.39)	(0.66)	(0.06)
Redemption		0.01	0.01	0.02	0.02	0.01	0.01
		(0.54)	(0.42)	(0.76)	(0.64)	(0.29)	(0.75)
Leverage		–0.03	–0.02	–0.04*	–0.04*	–0.02	–0.02
		(–1.46)	(–1.16)	(–1.67)	(–1.72)	(–1.34)	(–1.11)
Hurdle		–0.06	–0.06	–0.06	–0.06	–0.06	–0.05
		(–1.43)	(–1.63)	(–1.46)	(–1.47)	(–1.38)	(–1.49)
HWM		0.00	0.01	0.00	–0.01	0.01	0.01
		(–0.14)	(0.24)	(–0.21)	(–0.66)	(0.33)	(0.39)
Offshore		–0.02	–0.01	–0.02	–0.03	–0.01	0.00
		(–0.76)	(–0.39)	(–0.80)	(–1.09)	(–0.42)	(0.00)
Past return (12M)		1.62***	1.73***	1.63***	1.59***	1.84***	1.80***
		(5.68)	(7.33)	(5.30)	(6.67)	(7.36)	(6.51)
Ret VOL (24M)		4.04*	3.11*	4.37*	3.96**	3.15*	3.70***
		(1.65)	(1.87)	(1.93)	(2.06)	(1.94)	(2.68)
Ret SKEW (24M)		0.03	0.05**	0.02	0.04	0.05**	0.05*
		(0.92)	(2.03)	(0.68)	(1.22)	(2.20)	(1.91)
Ret KURT (24M)		0.00	0.00	–0.01	0.00	0.00	0.00
		(–0.39)	(–0.45)	(–0.55)	(–0.28)	(–0.24)	(–0.19)
β^{MKT}			0.21				0.33

			(0.98)				(1.51)
$\beta^{\Delta VOL}$				–0.01			0.05
				(–0.05)			(0.36)
$\beta^{\Delta SKEW}$				–0.91			–0.71*
				(–1.57)			(–1.69)
TailRisk					0.18		–0.09
					(1.08)		(–1.56)
β^{UNC}						0.03	0.01
						(1.64)	(0.76)
β^{RIX}						–0.01	–0.02
						(–0.14)	(–0.21)
R2						–0.08	–0.07
						(–0.68)	(–0.95)
SDI						–0.06	0.01
						(–0.86)	(0.13)
Downside Return						–0.02	–0.02
						(–0.60)	(–0.50)
Adjusted R^2	0.03	0.16	0.22	0.19	0.19	0.23	0.28

Table 2.6: H-Bear beta effect during market crashes versus normal times

The table shows results from Fama and Macbeth (1973) cross-sectional regressions of one-month ahead hedge fund excess returns on H-Bear beta (β^{H-BEAR}) and a series of control variables in different subperiods. The control variables included are the same with Specification (7) of Table 2.5. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. We present only the coefficients on H-Bear beta (β^{H-BEAR}) and market beta (β^{MKT}); the coefficients for the rest of the variables are suppressed for the sake of brevity. MKT denotes the excess return of the market. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Model	(1) MKT < P10	(2) MKT > P10	(3) MKT < 0	(4) MKT > 0
β^{H-BEAR}	–1.15***	–0.20*	–0.67***	–0.06
	(–2.75)	(–1.83)	(–2.62)	(–0.42)
β^{MKT}	–6.83***	1.13***	–2.61***	2.13***
	(–10.96)	(5.35)	(–7.40)	(6.21)
Control variables	Yes	Yes	Yes	Yes
Average adjusted R^2	0.43	0.27	0.30	0.28
Number of months	24	216	91	149

Table 2.7: H-Bear beta effect when bear market risk is (not) realized

The table shows results from Fama and Macbeth (1973) cross-sectional regressions of one-month ahead hedge fund excess returns on H-Bear beta (β^{H-BEAR}) and a series of control variables when bear market risk is realized versus when it is not realized. We define realized (unrealized) bear market risk periods as months with positive (negative) H-Bear factor returns. H-Bear factor is the component of the Bear factor that is orthogonal to the market excess returns. In month t, H-Bear return is equal to the intercept coefficient plus the month t residual from a regression of the Bear factor on the market excess returns over the past 24 months. The control variables included are the same with Specification (7) of Table 2.5. We present only the coefficients on H-Bear beta (β^{H-BEAR}) and market beta (β^{MKT}); the coefficients on other control variables are suppressed for the sake of brevity. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Model	(1) H-Bear factor < 0	(2) H-Bear factor > 0
β^{H-BEAR}	–0.49***	0.44***
	(–3.50)	(3.16)
β^{MKT}	0.04	1.41***
	(0.15)	(4.41)
Control variables	Yes	Yes
Average adjusted R^2	0.26	0.38
Number of months	189	51

Table 2.8: Sources of H-Bear factor exposure

The table presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund H-Bear beta (β^{H-BEAR}) on contemporaneous hedge fund exposures to feasible trading strategies over the period from December 1997 to November 2017. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. As feasible trading strategies, we use the Lu and Murray (2019) low minus high bear beta stocks (Stock-Bear), the Jurek and Stafford (2015) put-writing strategy, and the put-buying strategy which we design to invest in the market factor and simultaneously buy the SPX put option. We estimate a fund's exposure to the respective trading strategy using the past 24-month rolling window. We control for funds' exposures to the Fung and Hsieh (2004) trend-following factors, the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Gao, Gao, and Song (2018) RIX factor, and the Agarwal, Ruenzi, and Weigert (2017) tail risk. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Specification	(1)	(2)	(3)
Intercept	–0.02	–0.04**	–0.01*
	(–1.32)	(–2.18)	(–1.70)
$\beta^{Put-Writing}$ [Z = –1, L = 2]	–0.84***		–0.98***
	(–8.33)		(–9.16)
$\beta^{Put-Buying}$ [Z = –1, L = 2]	2.96***		3.10***
	(9.63)		(10.51)
$\beta^{Stock-Bear}$		–0.25***	–0.42**
		(–2.80)	(–2.18)
β^{PTFSBD}			0.16
			(0.39)
$\beta^{PTFSCOM}$			–0.70*
			(–1.91)
β^{PTFSFX}			0.95*
			(1.71)
β^{UNC}			2.92
			(1.27)
β^{RIX}			0.13**
			(2.16)
TailRisk			0.00
			(–0.18)
Adjusted R^2	0.51	0.11	0.83

Table 2.9: H-Bear factor exposure and hedge fund characteristics

The table presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund H-Bear beta (β^{H-BEAR}) on contemporaneous fund characteristics and risk attributes over the period from December 1997 to November 2017. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. A detailed definition of different fund characteristics and other measures of risks is provided in Appendix A1. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Specification	(1)	(2)	(3)
Intercept	0.00	–0.03	0.00
	(0.01)	(–0.63)	(–0.15)
Size	0.03		0.02
	(1.18)		(0.83)
Age	0.19*		0.17*
	(1.82)		(1.90)
Ret VOL (24M)	0.07		–0.16
	(0.18)		(–0.29)
Ret SKEW (24M)	0.10***		0.09***
	(6.00)		(5.89)
Ret KURT (24M)	0.00		0.00
	(–1.51)		(–1.56)
Fund return (12M)	–0.29**		–0.27**
	(–2.15)		(–2.30)
Min Investment		0.32	0.28
		(1.19)	(1.47)
Management Fee		–0.16**	–0.17**
		(–1.97)	(–2.24)
Incentive Fee		0.14*	0.08
		(1.85)	(1.05)
Lock Up		0.00	0.00
		(0.38)	(0.84)
Redemption		–0.01	0.00
		(–1.48)	(–0.32)
Leverage		0.01**	0.01*
		(2.15)	(1.68)
Hurdle		–0.04***	–0.02**
		(–2.73)	(–1.98)
HWM		0.01	0.01
		(1.08)	(1.17)
Offshore		–0.04***	–0.03***
		(–2.73)	(–3.05)
Adjusted R^2	0.14	0.03	0.16

Table 2.10: Long-term predictive power of H-Bear factor exposure

The table reports the long-term performance of H-Bear beta-sorted hedge fund quintle portfolios. All portfolios are equal-weighted. Panel A presents results for the H-Bear beta-sorted quintile portfolios with holding periods ranging from 3 months to 24 months. We implement the independently managed portfolio strategy of Jegadeesh and Titman (1993) to deal with the overlapping nature of the long-horizon returns and compute average monthly excess returns. We report the monthly average returns for each quintile as well as the average return and Fung-Hsieh alpha differences for the Q5–Q1 portfolio. In Panel B, we perform the same analysis as in Panel B except that we leave a one-month gap between the portfolio formation month and the month in which portfolio returns start being calculated. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Predictive power of H-Bear beta for long-term holding period returns

Holding for the next	3 months	6 months	9 months	12 months	15 months	18 months	21 months	24 months
Q1 (Low β^{H-BEAR})	0.87	0.83	0.80	0.76	0.74	0.70	0.67	0.64
Q2	0.56	0.55	0.56	0.55	0.54	0.52	0.52	0.50
Q3	0.47	0.46	0.49	0.48	0.48	0.46	0.45	0.44
Q4	0.41	0.41	0.47	0.47	0.46	0.44	0.43	0.42
Q5 (High β^{H-BEAR})	0.29	0.35	0.46	0.46	0.48	0.46	0.46	0.46
Q5–Q1	–0.58***	–0.49***	–0.34***	–0.30***	–0.27***	–0.23***	–0.21***	–0.18**
	(–3.53)	(–3.79)	(–2.99)	(–3.18)	(–3.28)	(–2.97)	(–2.63)	(–2.30)
FH alpha	–0.71***	–0.58***	–0.39***	–0.34***	–0.29***	–0.25**	–0.23**	–0.19*
	(–3.66)	(–3.89)	(–3.15)	(–3.05)	(–2.65)	(–2.35)	(–2.14)	(–1.88)

Panel B: Long-term holding period with a 1-month lag between ranking and performance months

1-month lag and holding for the next	3 months	6 months	9 months	12 months	15 months	18 months	21 months	24 months
Q1 (Low β^{H-BEAR})	0.84	0.79	0.75	0.72	0.70	0.68	0.66	0.64
Q2	0.57	0.55	0.54	0.54	0.53	0.53	0.53	0.52
Q3	0.48	0.47	0.47	0.47	0.47	0.47	0.47	0.48
Q4	0.42	0.43	0.44	0.44	0.44	0.45	0.45	0.46
Q5 (High β^{H-BEAR})	0.34	0.39	0.43	0.46	0.48	0.50	0.51	0.53
Q5–Q1	–0.50***	–0.40***	–0.32***	–0.26***	–0.22***	–0.18**	–0.15*	–0.11
	(–3.55)	(–3.66)	(–3.35)	(–2.97)	(–2.64)	(–2.20)	(–1.75)	(–1.28)
FH alpha	–0.62***	–0.51***	–0.42***	–0.36***	–0.31***	–0.28***	–0.25**	–0.21**
	(–3.82)	(–3.98)	(–3.87)	(–3.47)	(–3.08)	(–2.77)	(–2.41)	(–2.02)

Table 2.11: Performance of H-Bear beta-sorted hedge fund portfolios in different investment style categories
The table reports the performance of H-Bear beta-sorted hedge fund portfolios for each investment style. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from December 1997 to November 2017, hedge funds of a specific investment style are sorted into five portfolios on the basis of their H-Bear betas. Quintile 1 (5) consists of funds with the lowest (highest) H-Bear betas. We rebalance the portfolios each month; thus, the portfolio returns are from January 1998 to December 2017. For each style, we present the average H-Bear beta, the average equal-weighted return and Fung-Hsieh alpha (in percentage terms) for each quintile as well as for the Q5–Q1 portfolio. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Q1	Q2	Q3	Q4	Q5	Q5–Q1
			Event-Driven			
Average H-Bear Beta	–0.43	–0.14	–0.04	0.07	0.41	0.84
Return	0.82	0.55	0.55	0.48	0.47	–0.35***
	(4.51)	(4.21)	(4.77)	(3.15)	(2.25)	(–2.83)
FH alpha	0.58	0.37	0.40	0.30	0.17	–0.41***
	(4.95)	(4.21)	(5.17)	(2.67)	(1.78)	(–3.54)
			Relative Value			
Average H-Bear Beta	–0.47	–0.13	–0.03	0.06	0.34	0.80
Return	0.92	0.63	0.50	0.35	0.20	–0.72***
	(5.30)	(6.29)	(5.31)	(2.72)	(0.96)	(–3.05)
FH alpha	0.78	0.55	0.41	0.24	0.02	–0.76***
	(4.85)	(6.93)	(5.98)	(2.39)	(0.11)	(–2.96)
			Long-Short Equity			
Average H-Bear Beta	–0.76	–0.23	–0.02	0.18	0.69	1.44
Return	0.86	0.64	0.59	0.56	0.61	–0.25*
	(3.37)	(3.57)	(3.59)	(2.95)	(2.47)	(–1.80)
FH alpha	0.46	0.29	0.25	0.14	0.12	–0.35**
	(2.27)	(2.19)	(2.43)	(1.46)	(0.87)	(–2.17)
			Global Macro			
Average H-Bear Beta	–0.62	–0.19	0.00	0.18	0.65	1.27
Return	0.92	0.76	0.49	0.41	0.22	–0.70***
	(4.93)	(4.96)	(3.59)	(3.19)	(0.80)	(–3.31)
FH alpha	0.79	0.61	0.35	0.28	0.02	–0.77***
	(4.14)	(4.11)	(2.37)	(2.33)	(0.09)	(–4.18)
			CTA			
Average H-Bear Beta	–0.56	–0.15	0.02	0.20	0.76	1.32
Return	0.70	0.38	0.25	0.24	0.18	–0.52***
	(4.19)	(2.55)	(2.26)	(3.11)	(1.09)	(–2.98)
FH alpha	0.68	0.35	0.26	0.25	0.15	–0.53***
	(4.27)	(2.18)	(2.43)	(2.99)	(0.80)	(–2.81)
			Equity Market-Neutral			
Average H-Bear Beta	–0.34	–0.12	–0.02	0.08	0.36	0.70
Return	0.42	0.32	0.29	0.23	0.22	–0.21**

	(6.74)	(6.98)	(6.49)	(3.21)	(2.65)	(–2.47)
FH alpha	0.36	0.26	0.26	0.17	0.15	–0.21**
	(4.74)	(5.75)	(5.14)	(2.49)	(1.99)	(–2.06)
			Multi-Strategy			
Average H-Bear Beta	–0.60	–0.18	0.01	0.19	0.70	1.29
Return	0.92	0.67	0.48	0.39	0.31	–0.61***
	(5.26)	(5.26)	(5.95)	(4.64)	(2.50)	(–2.99)
FH alpha	0.97	0.68	0.45	0.34	0.26	–0.71***
	(4.35)	(4.01)	(4.46)	(3.76)	(2.13)	(–2.94)
			Sector			
Average H-Bear Beta	–0.53	–0.12	0.10	0.34	0.94	1.47
Return	1.10	0.62	0.76	0.59	0.51	–0.58**
	(2.67)	(2.41)	(2.07)	(1.82)	(1.43)	(–2.01)
FH alpha	0.64	0.28	0.38	0.16	0.00	–0.64*
	(1.96)	(1.25)	(1.26)	(0.64)	(–0.01)	(–1.94)
			Fund of Funds			
Average H-Bear Beta	–0.31	–0.12	–0.05	0.03	0.22	0.53
Return	0.53	0.46	0.41	0.39	0.25	–0.28***
	(3.96)	(3.57)	(3.22)	(2.75)	(1.71)	(–3.68)
FH alpha	0.39	0.31	0.26	0.24	0.07	–0.32***
	(3.09)	(2.81)	(2.49)	(2.04)	(0.67)	(–3.28)

Table 2.12: H-Bear beta versus skills at exploiting rare disaster concern

The table investigates the difference between H-Bear beta and skills at exploiting rare disaster concern. For consistency with Gao, Gao, and Song (2018), all findings are based on the period from January 1998 to December 2011. Panel A reports the performance of decile portfolios of hedge funds sorted by the betas (or sensitivities) with respect to various versions of the RIX index over the full sample period and conditional on market crashes (MKT < P10) versus normal times (MKT > P10). These betas are estimated by regressing hedge fund excess returns on different versions of the RIX index controlling for the market excess returns over a 24-month rolling window. At the end of each month from December 1997 to November 2011, we sort hedge funds into deciles according to their betas on different versions of the RIX index. We rebalance the portfolios each month; thus, the portfolio returns are from January 1998 to December 2011. We measure the average equal-weighted returns for several decile portfolios and for D10–D1 portfolio. We present four sets of results. Specification (1) uses the RIX index that is made publicly available by George Gao. Specification (2) uses our replicated RIX index. Specification (3) uses a RIX index which is constructed from S&P 500 put options. Specification (4) uses RETRIX, which is the average daily return within a month of a portfolio of S&P 500 index put options that form RIX. Panel B reports the performance of hedge fund portfolios that are sorted on RIX betas and RETRIX betas. In Panel B.1, we first sort funds based on RETRIX betas into quintiles and within each quintile, we further sort funds into five portfolios based on RIX betas. In Panel B.2, we first sort funds based on RIX betas into quintiles and within each quintile, we sort funds into five portfolios based on RETRIX betas. We rebalance these portfolios each month and report equal-weighted as well as risk-adjusted returns. All returns and alphas are in monthly percentages. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Univariate portfolio-level analysis, sorted on betas with respect to various versions of the RIX index

	Full sample: Jan 1998 – Dec 2011					MKT < P10			MKT > P10		
	D1	D5	D10	D10–D1	FH alpha	D1	D10	D10–D1	D1	D10	D10–D1
(1) Sort by fund's sensitivity to RIX index obtained from Gao et al. (2018)											
Returns (%)	0.34	0.43	1.11	0.77**	0.80***	–5.43	–1.48	3.94**	1.00	1.41	0.42**
	(0.91)	(2.47)	(4.57)	(2.51)	(3.11)	(–4.10)	(–2.28)	(2.42)	(3.90)	(5.78)	(1.96)
(2) Sort by fund's sensitivity to our replicated RIX index											
Returns (%)	0.32	0.44	1.04	0.72**	0.83***	–5.79	–1.32	4.47***	1.04	1.36	0.32
	(0.77)	(2.65)	(4.80)	(2.17)	(3.09)	(–4.50)	(–2.25)	(3.06)	(3.90)	(5.78)	(1.43)
(3) Sort by fund's sensitivity to our replicated RIX index that uses only options from S&P 500											
Returns (%)	0.44	0.48	0.95	0.52	0.64**	–5.10	–1.62	3.48*	1.11	1.28	0.17
	(1.05)	(2.88)	(4.50)	(1.47)	(2.16)	(–3.45)	(–1.91)	(1.67)	(3.97)	(5.91)	(0.79)
(4) Sort by fund's sensitivity to RETRIX											
Returns (%)	1.10	0.47	0.35	–0.75***	–0.83***	–2.41	–4.09	–1.69**	1.51	0.87	–0.64***
	(4.07)	(2.91)	(1.15)	(–2.98)	(–2.87)	(–9.35)	(–7.97)	(–2.33)	(6.04)	(4.01)	(–3.71)

Panel B: Bivariate dependent portfolio–level analysis, sorted on RIX betas and RETRIX betas

Panel B.1: First sort on RETRIX betas, then on RIX beta

	Low β^{RIX}	2	3	4	High β^{RIX}	Q5–Q1	FH alpha
Low β^{RETRIX}	0.71	0.72	0.65	0.88	1.37	0.66** (2.19)	0.63** (2.14)
2	0.46	0.51	0.51	0.54	0.77	0.31* (1.73)	0.32** (2.01)
3	0.51	0.47	0.39	0.50	0.71	0.20 (1.46)	0.21 (1.58)
4	0.40	0.42	0.39	0.49	0.75	0.35** (2.06)	0.41*** (2.86)
High β^{RETRIX}	0.23	0.36	0.27	0.55	0.75	0.52* (1.84)	0.62** (2.40)
Average	0.46	0.50	0.44	0.59	0.87	0.41** (2.13)	0.44*** (2.65)

Panel B.2: First sort on RIX betas, then on RETRIX betas

	Low β^{RETRIX}	2	3	4	High β^{RETRIX}	Q5–Q1	FH alpha
Low β^{RIX}	0.76	0.48	0.35	0.30	0.13	–0.63** (–2.00)	–0.83** (–2.10)
2	0.65	0.53	0.46	0.41	0.40	–0.26* (–1.70)	–0.39** (–2.54)
3	0.60	0.45	0.43	0.40	0.35	–0.25** (–2.45)	–0.33*** (–2.83)
4	0.75	0.62	0.50	0.54	0.44	–0.31** (–2.50)	–0.36*** (–2.80)
High β^{RIX}	1.31	0.96	0.76	0.76	0.79	–0.52*** (–2.73)	–0.62*** (–3.30)
Average	0.81	0.61	0.50	0.48	0.42	–0.39*** (–2.65)	–0.51*** (–2.99)

Table 2.13: Robustness checks

The table reports the results from a series of robustness checks with respect to the average returns and Fung-Hsieh alphas of hedge fund portfolios sorted by H-Bear beta. At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles according to their H-Bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) H-Bear betas. We hold these quintile portfolios for one month and present the average returns and alphas for each quintile and for the Q5–Q1 portfolio. In Specification (1), average returns are weighted by the fund's AUM at the time of portfolio formation. In Specifications (2) and (3), H-Bear beta is estimated over the 12-month and 36-month rolling window, respectively. In Specifications (4) and (5), we construct the Bear portfolio by defining the bear region as states in which the market excess return is two and one standard deviations below zero, respectively. In Specification (6), we drop the short put position from the Bear portfolio and use only the long put position. In Specification (7), we adopt the methodology in Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns. In Specification (8), we set –100% on returns of drop-out funds. In Specification (9), we use the manipulation-proof performance measure (MPPM) with a penalizing coefficient of three (see Goetzmann, Ingersoll, Spiegel, and Welch, 2007). All returns and alphas are in monthly percentages. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Q1	Q2	Q3	Q4	Q5	Q5–Q1
(1) Value-weighted returns						
Value-weighted returns	0.83	0.52	0.44	0.40	0.20	–0.63***
	(6.01)	(4.74)	(4.38)	(3.31)	(1.30)	(–3.42)
FH alpha	0.67	0.38	0.30	0.22	–0.06	–0.73***
	(4.38)	(4.20)	(4.03)	(2.50)	(–0.51)	(–3.40)
(2) Horizon of 12 months						
Equal-weighted returns	0.88	0.57	0.51	0.47	0.39	–0.50***
	(5.52)	(4.91)	(4.26)	(3.42)	(1.69)	(–2.75)
FH alpha	0.69	0.41	0.33	0.24	0.01	–0.67***
	(4.56)	(4.69)	(4.18)	(2.82)	(0.10)	(–3.36)
(3) Horizon of 36 months						
Equal-weighted returns	0.82	0.56	0.48	0.44	0.39	–0.42***
	(5.96)	(5.20)	(4.30)	(3.66)	(2.67)	(–4.30)
FH alpha	0.58	0.39	0.32	0.26	0.12	–0.46***
	(3.51)	(3.32)	(2.93)	(2.61)	(1.24)	(–3.38)
(4) $\beta_{2\sigma}^{H-BEAR}$						
Equal-weighted returns	0.81	0.52	0.46	0.46	0.38	–0.43***
	(4.83)	(4.74)	(4.00)	(3.63)	(2.26)	(–3.16)
FH alpha	0.61	0.35	0.30	0.26	0.09	–0.52***
	(3.57)	(3.89)	(3.28)	(2.94)	(0.96)	(–3.18)
(5) $\beta_{1\sigma}^{H-BEAR}$						
Equal-weighted returns	0.84	0.57	0.47	0.42	0.33	–0.51***
	(5.50)	(4.97)	(4.00)	(3.20)	(1.85)	(–3.65)
FH alpha	0.69	0.42	0.31	0.21	0.00	–0.69***
	(4.10)	(3.88)	(3.33)	(2.31)	(–0.05)	(–4.09)
(6) β^{H-PUT}						
Equal-weighted returns	0.80	0.56	0.48	0.43	0.35	–0.45***
	(4.71)	(4.61)	(4.07)	(3.42)	(2.36)	(–3.54)
FH alpha	0.60	0.40	0.32	0.22	0.07	–0.53***

	(3.71)	(3.69)	(3.39)	(2.61)	(0.80)	(–3.30)
(7) Unsmoothing returns						
Equal-weighted returns	0.85	0.55	0.46	0.46	0.30	–0.55***
	(5.29)	(4.81)	(3.89)	(3.39)	(1.72)	(–3.62)
FH alpha	0.65	0.37	0.27	0.22	–0.03	–0.68***
	(3.75)	(3.49)	(2.92)	(2.34)	(–0.29)	(–3.62)
(8) Delisting returns						
Equal-weighted returns	–0.18	–0.35	–0.46	–0.59	–0.99	–0.80***
	(–0.92)	(–1.97)	(–2.34)	(–3.20)	(–3.91)	(–4.41)
FH alpha	–0.37	–0.52	–0.63	–0.79	–1.30	–0.93***
	(–1.95)	(–2.98)	(–3.43)	(–4.87)	(–7.41)	(–4.46)
(9) MPPM						
Equal-weighted MPPM	0.02	0.03	0.02	0.02	–0.01	–0.03***
	(1.21)	(2.54)	(1.94)	(1.23)	(–0.70)	(–3.65)

Chapter 3

Is firm-level political risk priced in the equity option market?

3.1. Introduction

Uncertainty associated with possible changes in government policies and their future impacts can significantly affect the risk perceptions of capital market participants. Pástor and Veronesi (2012, 2013) build a theoretical framework in which investors demand a risk premium as compensation for political uncertainty. Motivated by the fact that options constitute ideal securities for isolating and studying various risk premiums, Kelly et al. (2016) extend this framework and find that options whose lives span political events such as national elections and global summits tend to be more expensive as they provide protection against the risks associated with those events. However, their study relies on index options and variation in aggregate political risk. There are two main reasons for which it is important to investigate the existence of a respective pricing effect at the individual firm level.

First, the market-wide risks associated with major political events are typically easy to analyze. For example, it seems straightforward that investors were well-aware of the summits that took place in 2010 due to the Greek crisis and had adjusted their portfolios beforehand in order to hedge against potential adverse market reactions and increases in volatility. As Hassan et al. (2019) (HHLT henceforth) illustrate in their seminal paper, however, firm-level political risk is much more difficult to be quantified and is also more heterogeneous and volatile than previously thought.[1] Instead of having an economy-wide effect, a certain policy may affect a particular sector, state, or demographic group. Similarly, firms with different business and operating characteristics tend to respond differently to a particular political decision. For example, a new climate policy might be harmful for a coal-intensive energy firm but beneficial for a photovoltaics company, while a new state regulation is expected to affect disproportionately firms with a higher percentage of their sales coming from the given state. Therefore, it is less clear whether investors conceive the complex relations surrounding firm-level political risk, and, if they do, how they trade in anticipation of this multifaceted type of uncertainty. Overall, by focusing on firm- rather than aggregate-level political risk we can get a much more granular picture of whether and how political risk is priced, especially given that firm-level effects can be concealed when aggregated at the overall market level.

Second, the fact that political risk is priced in the context of the index option market does not mean that this relation necessarily holds for the equity option market too. In fact, there is abundant evidence that the two markets are rather segmented and exhibit significant differences in terms of trading activity and investor composition. For example, the index option market has a higher percentage of firm proprietary investors than the equity option market, and its end-user demand refers more to put rather than call options as is the case for the equity option market (Bollen and Whaley, 2004; Pan and Poteshman, 2006; Lakonishok et al., 2007; Lemmon and Ni, 2014). Such differences in trading patterns are also accompanied by differences in the pricing effects prevalent in the two markets. Bakshi et al. (2003) show that equity options are associated with less negative risk-neutral skewness values than index options. Importantly, Bakshi and Kapadia (2003b) and Carr and Wu (2009) find that equity option returns are lower – in absolute terms – than index option

[1]As an anecdotal example of firm-specificity in political risk, President Trump consistently criticized Amazon for avoiding taxes, ripping off the US Postal Service and using Washington Post newspaper as a “lobbyist”. When the Defense Department surprised analysts by awarding a $10 billion Defense Infrastructure project to Microsoft in October 2019, Amazon claimed that President Trump used “improper pressure” on the Pentagon to prevent Amazon from winning the contract.

returns, while Driessen et al. (2009) show that correlation risk is priced in index options but not in equity options. This means, for example, that if political risk is priced at the aggregate level mainly because it increases the correlation among stocks (Pástor and Veronesi, 2012), then it is likely that it is not priced at the individual firm level. Overall, given the important differences in the two markets, it remains an open empirical question whether political risk matters for individual stock options.

In this chapter, we find that firm-level political risk exhibits strong negative predictive power for the cross-section of delta-hedged equity option returns (i.e., option returns that are immune to underlying asset price movements). This implies that investors are willing to pay higher prices for the options of politically risky firms (i.e., the implied volatility of options is higher than their realized volatility) and earn lower future option returns, consistent with the notion that options – due to their embedded leverage, as well as vega and gamma exposure – increase in value in case of severe stock price movements caused by political incidents. Importantly, we find that this effect is driven by both hedgers and speculators corroborating HHLT's (2019) evidence that individual firms might be both positively and/or negatively affected by political decisions. Overall, our results lend credence to the notion that political risk is to a large extent a firm-specific phenomenon which is priced even without having a homogeneous or systematic effect across stocks. In addition, we challenge the prevailing view that political uncertainty is only regarded as something unfavourable by investors and, accordingly, we are the first to delineate the political risk-motivated trading activities of different investor groups.

For our empirical exercises we use a comprehensively validated measure of firm-level political risk, $PRisk$, developed by HHLT (2019).[2] HHLT (2019) perform a textual analysis of each firm's quarterly earnings conference calls and quantify firm-level political risk based on the percentage of the conversation about politics surrounding a synonym of risk or uncertainty. Thus, the

[2]HHLT (2019) validate their firm-level political risk measure by showing that it has a significant positive association with implied volatility. However, a high implied volatility alone does not necessarily indicate option mispricing, nor does it give any concrete information about the future delta-hedged option return. For example, the delta-hedged return of an option with high implied volatility will be positive if future stock volatility is even higher.

construction of this political risk measure is completely determined by the exchange of information among financial market participants and is entirely independent from stock or option prices. Moreover, it is different from other aggregate political uncertainty measures such as Baker et al.'s (2016) measure of economy-wide policy uncertainty (EPU) or election-based uncertainty measures. In fact, HHLT (2019) show that around 90% of the total variation in their measure of political risk occurs at the firm level, while the variation in aggregate political risk over time accounts for only 1%. They further emphasize that the firm-level variation in political risk is not explained by differential exposure to aggregate political risk.

Following Cao and Han (2013), our analysis relies on the returns of long call and put option positions that are delta-hedged on a daily basis with the appropriate number of underlying shares. This procedure ensures that our findings on option returns are not driven by the options' directional exposure to the underlying stocks. Using a Fama and MacBeth (1973) cross-sectional regression analysis we find that firm-level political risk is significantly and negatively associated with future delta-hedged option returns. The relation remains significant after controlling for various firm-related characteristics, such as size, idiosyncratic volatility, stock illiquidity, institutional ownership etc. We confirm the cross-sectional regression findings using a panel regression approach which yields comparable results in terms of the effect sizes and significance levels. The results are also robust to alternative measurements and definitions of option returns. In addition, the negative association between political risk and option returns cannot be explained by volatility mispricing or uncertainty, higher-order risk-neutral moments, jump risk, or option illiquidity. Via a portfolio-sorting analysis, we document a decrease of about 30 bps in option returns when we move from the low- to the high-political risk quintile portfolio. This analysis further reveals that the political risk effect is robust throughout the sample period and is more strongly driven by high-political risk firms. Overall, across different specifications, we consistently find that cross-sectional heterogeneity in firm-level political risk explains future equity option returns.

In a next step, we investigate potential economic channels that might drive the negative relation between firm-level political risk and delta-hedged option returns. First, a series of studies (e.g., Bollen and Whaley, 2004; Gârleanu et al. 2009) suggest that, in the presence of market imperfections, markets makers face inventory risk and hence charge a higher premium when option demand grows large. Motivated by the idea that investors might use options to hedge against negative or speculate on positive price movements stemming from political shocks, we examine a demand-based explanation of our findings.[3] Consistent with such an explanation, we find that politically risky firms experience increased call and put option demand and that the association between political risk and future option returns is more pronounced when option demand is elevated. In addition, we use signed option volume data from the International Securities Exchange to compute option net buying pressure across different investor groups and option categories. We show that high-political risk firms are associated with significantly higher out-of-the-money call buying pressure on the part of public customers (e.g., retail investors and hedge funds) and higher out-of-the-money put buying pressure on the part of firm proprietary investors (i.e., large institutions trading for their own accounts). Overall, it appears that speculative call option demand stemming from customers and hedging put option demand stemming from firm proprietary investors are major drivers of the political risk-option return relation.[4,5]

Second, political risk has been shown to intensify the information uncertainties and asymmetries that already exists in the market. For example, firms might release more obfuscated information during politically uncertain times, while some investors might be better informed due to their political connections (Chen et al., 2018; Jagolinzer et al., 2020). Such situations are likely to create model risk for the market makers and hence to increase their difficulty in dynamically hedging options (Figlewski, 1989; Green and Figlewski, 1999). Therefore, we hypothesize that in an opaque information environment risk-averse market makers require even higher compensation for

[3]Note that firm-level political uncertainty can be also related to the upside and not only to the downside. For example, changes in medical reimbursement policies can affect the profits of healthcare firms either negatively or positively (Koijen et al., 2016).

[4]The motive for buying a put option is to hedge a long stock position and/or to obtain protection against an increase in volatility that is usually accompanied by a price drop in the underlying (the so-called leverage effect).

[5]Pan and Poteshman (2006) provide evidence consistent with the notion that in the equity option market public customers act as informed speculators and firm proprietary traders act as hedgers.

supplying options on politically risky firms (at the same time, end-users willingly pay such high prices due to their speculative or hedging motives). Using various proxies for information uncertainty, we find that, in line with our hypothesis, the negative effect of political risk on delta-hedged option returns is stronger among the group of high-information uncertainty firms.

Third, we offer a complementary explanation of our empirical results based on option valuation arguments. Vasquez and Xiao (2020) provide theoretical evidence linking distress risk to the volatility risk premium, while Bakshi and Kapadia (2003a) show that – within a stochastic volatility environment – the volatility premium is the main driver of delta-hedged option returns. Moreover, several recent studies underline that political uncertainty and interference can impact a firm's financial health (e.g., Kaviani et al., 2020; Gad et al., 2021). Motivated by the above two literatures, we examine whether political risk affects option returns by amplifying the distress risk-driven part of the volatility risk premium. We find that the predictive power of political risk for option returns is stronger among high-default probability firms, thus providing support to our conjectured economic mechanism.[6]

We proceed to explore whether firms who actively engage in the political process by lobbying politicians or by donating to election campaigns can mitigate the price impact of political risk on options. Consistent with the notion that political activism can reduce uncertainty, lobbying and political donations are associated with a significantly less negative relation between political risk and expected delta-hedged option returns. Furthermore, we find that this mitigating role of political activism stems from non-partisan firms, i.e., those firms that hedge against political risk by donating simultaneously to both parties, rather than from partisan firms, i.e., those firms that greatly tilt their donations towards a single party. The documented conditioning role of lobbying and donations for the political risk-option returns relation provides further evidence in favor of a unique pricing impact of political risk that is different from that of idiosyncratic volatility, for example.

[6]Given our empirical evidence with respect to the political risk-induced trading activity of different investor groups, this economic mechanism can be mainly used to describe an equilibrium between firm proprietary traders and market makers.

In addition to the cross-sectional relation between political risk and option returns, we investigate the respective time-series relation by studying how option returns respond to unexpected increases or decreases in firm-level political risk after earnings conference calls. We find that, when there is a positive surprise in political risk, delta-hedged option returns decrease after the earnings call. The differences between post-event and pre-event option returns are −11 bps and −12 bps for call and put options, respectively. We also observe an opposite effect, i.e., that option returns increase after an unexpected decrease in firm-level political risk, but this effect is not statistically significant. Overall, this evidence is consistent with the idea that, as new information about a firm's political risk is revealed during an earnings call, investors adjust their expectations and accept lower option returns after an increase in the firm's political risk level.

Finally, we explore whether there is a significant heterogeneity across the risk premiums associated with firm-level political risk based on eight different topics, namely economic policy, environment, trade, institutions, healthcare, security, taxation, and technology. We find that, while all aspects of political risk are priced in the option market, the intensity of the effect varies significantly across topics. During our sample period political uncertainty related to healthcare earns the highest risk premium.

Our study makes several contributions to the existing literature. First, it is related to a series of studies that use the EPU index and election events or cycles to examine the association between aggregate political risk and the outcomes of various financial markets, such as the stock, credit, option, CDS, and commodity market (Pástor and Veronesi, 2013; Belo et al., 2013; Brogaard and Detzel, 2015; Baker et al., 2016; Kelly et al., 2016; Liu et al., 2017; Liu and Zhong, 2017; Wang et al., 2019; Kaviani et al., 2020; Hou et al., 2020). However, as previously mentioned, economy-wide political risk masks a large proportion of the variation in political risk across firms but also across time for each given firm. Accordingly, we contribute to the infant literature that examines the impact of firm-specific political risk on asset prices. Gad et al. (2021) investigate the effect of political risk on a broad set of credit market outcomes, Saffar et al. (2019) study its effect on bank loan contracting, while Gorbatikov et al. (2019) find that it is priced in the equity market. Different from these papers, we focus on the option market in order to understand investors' preferences towards politics-induced volatility risk.

Second, our work extends prior studies that analyze the cross-section of individual stock option returns. Cao and Han (2013) and Hu and Jacobs (2020) study the impact of stock volatility on delta-hedged and raw option returns, respectively. Goyal and Saretto (2009) suggest that the difference between implied volatility and past stock return volatility exhibits cross-sectional predictive power because it reflects investors' misestimation of volatility dynamics. Vasquez (2017) and Cao et al. (2019) identify the volatility term structure and the volatility-of-volatility, respectively, as strong predictors of option returns, while Cao et al. (2021) show that a large number of stock characteristics serve as powerful predictors too. Another literature stream focuses on the skewness preference of investors and its effect on the returns of various option portfolios (Bali and Murray, 2013; Boyer and Vorkink, 2014; Byun and Kim, 2016).[7] Most of the earlier option return predictors are derived from option and stock price data that are observable in the market. In contrast, our suggested option return predictor, political risk, is an intangible concept that is reflected in the conversations among market participants during conference calls.

The rest of the chapter proceeds as follows. Section 3.2 describes the data for option returns and the firm-level political risk measure. Section 3.3 reports our main findings and provides robustness checks. Section 3.4 explores various economic mechanisms that may generate the relation between political risk and option returns. Section 3.5 presents further analyses that shed more light on the economic nature of the documented relation. Finally, Section 3.6 provides concluding remarks.

[7]Other studies that investigate return predictability in the equity option market include An et al. (2014), Christoffersen et al. (2018), Gao et al. (2018), Vasquez and Xiao (2020), Eisdorfer et al. (2020), Eisdorfer et al. (2021), Andreou et al. (2021).

3.2. Data and variables

3.2.1. Data

Our data comes from several sources. Data for firm-level political risk is generously provided by HHLT (2019). We obtain data for all U.S. individual stock options including daily closing bid and ask quotes, trading volume, open interest, implied volatilities and various Greeks for each option from the Ivy DB database provided by Optionmetrics. We include options for securities which are listed as common stocks (share codes 10 and 11) and are traded on NYSE, AMEX, or NASDAQ (exchange codes 1, 2, and 3). Underlying stock prices and returns are downloaded from CRSP. Relevant accounting information is collected from Compustat. Further, we obtain analyst coverage and forecast data from IBES. Due to the availability of the political risk measure, our sample covers the period from January 2003 to June 2019.

3.2.2. Variables

3.2.2.1. Delta-hedged option returns

Given that an option is a derivative on a stock, option returns are highly correlated with stock returns. We follow Bakshi and Kapadia (2003a) and Cao and Han (2013) to calculate the gain of a delta-hedged option position as the change in the value of a self-financing portfolio containing a long call (put) option, hedged by a short (long) position in the underlying stock. This portfolio gain is not sensitive to the underlying stock price movement and the net investment earns the risk-free rate.

Consider a call option that is hedged discretely N times over a period $[t, t+\tau]$, where the hedge is rebalanced at each of the dates $\mathrm{t_n}$, with $\mathrm{n} = 0, 1, \ldots, \mathrm{N}-1$, $\mathrm{t_0} = \mathrm{t}$ and $\mathrm{t_N} = \mathrm{t} + \tau$. The gain of a discretely delta-hedged call option in excess of the risk-free rate is given by:

$$\prod(\mathrm{t}, \mathrm{t}+\tau) = \mathrm{C_{t+\tau}} - \mathrm{C_t} - \sum_{\mathrm{n}=0}^{\mathrm{N}-1} \triangle_{C,t_n} [S(t_{n+1}) - S(t_n)] - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} [C(t_n) - \triangle_{C,t_n} S(t_n)], \quad (3.1)$$

where C_t is the call option price on date t, $\triangle_{C,t_n}$, $S(t_n)$ and r_{t_n} are the delta of the call option, the underlying stock price, and the annualized risk-free rate on date t_n, respectively, and a_n is the number of calendar days between t_n and t_{n+1}. The delta-hedged put option gain is calculated by replacing in Equation (1) the call price and call delta with the put price and put delta.

At the end of each month and for each optionable stock, we select one call and one put option that are the closest to being at-the-money and have the shortest maturity among the options with more than one month to maturity. We hedge the call and put option on a daily basis until the end of next month. To make the delta-hedged option returns comparable across different stocks, we calculate the delta-hedged call option return as the scaled delta-hedged call option gain, $\prod(t, t+\tau)\,/(\triangle_t\, S_t - C_t)$, and the delta-hedged put option return as the scaled delta-hedged put option gain, $\prod(t, t+\tau)\,/(P_t - \triangle_t\, S_t)$. The scaling factors $(\triangle_t\, S_t - C_t)$ and $(P_t - \triangle_t\, S_t)$ represent the total value of the initial position in stocks and options.

We apply several filters to the extracted option data following Cao and Han (2013). First, to avoid illiquid options, we exclude options if the trading volume is zero, if the open interest is zero or missing, if the bid quote is zero, if the bid quote is larger than the ask quote, or if the average of the bid and ask price is lower than 1/8. Second, we discard options whose underlying stock pays a dividend during the remaining life of the option in order to remove the effect of the early exercise premium in American options. As a result, the options in our sample are close to European style options. Third, we exclude all options that violate no arbitrage conditions.[8] Fourth, we only keep options with moneyness higher than 0.8 and lower than 1.2. Only options whose last trading dates match the record dates are retained. Finally, following Cao et al. (2021), we only keep firms with both call and put options available after filtering.

[8]Specifically, for call options we require that the underlying price exceeds the option price, which is in turn higher than $max\left(0, S_t - K_t e^{-r(t+\tau)}\right)$; for put options we require that the discounted exercise price exceeds the option price, which is in turn higher than $max\left(0, K_t e^{-r(t+\tau)} - S_t\right)$.

3.2.2.2. Firm-level political risk

HHLT (2019) create a text-based measure of firm-level political risk by applying a computational linguistics algorithm to the public transcripts of the quarterly earnings conference calls of listed US firms. In these conference calls, senior management and market participants discuss about topics that affect the firm's financial performance. First, HHLT (2019) develop a training library of political texts, $\mathbb{P}$, using an undergraduate political science textbook, supplemented with texts from the political sections of newspapers, and a training library of non-political texts, $\mathbb{N}$, using financial accounting textbooks and texts from newspapers' financial sections. Then, a determination of words that signal political topics is achieved by comparing the adjacent two-word combination bigrams from these training libraries. Finally, the political risk measure is constructed by counting the number of exclusive political bigrams surrounding a synonym for risk or uncertainty and dividing it by the total number of bigrams in the transcript (to adjust for the transcript's length):

$$PRisk_{i,t} = \frac{\sum_{b}^{B_{i,t}} \left(1[b \in \mathbb{P} \backslash \mathbb{N}] \times 1[|b - r| < 10] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \right)}{B_{i,t}} , \tag{3.2}$$

where $1[\dots]$ is the indicator function, $\mathbb{P}\backslash\mathbb{N}$ is the sets of bigrams contained in $\mathbb{P}$ but not $\mathbb{N}$, r is the position of the nearest synonym of risk and uncertainty, $b = 1, \dots, B_{i,t}$ is the number of bigrams in the call transcript, $f_{b,\mathbb{P}}$ is the frequency of bigram b in the political training library, and $B_{\mathbb{P}}$ is the total number of bigrams in the political training library. HHLT (2019) subject their political risk measure to a range of validity checks, including (1) human verification, (2) alignment with political events over time and political sensitivity check for some industries during these events, (3) association between political risk and firm outcomes that are likely affected by political risk, and (4) tests verifying the distinction between political risk and non-political risk.

Overall, the political risk measure captures the proportion of the conversation devoted to risks related to political (rather than non-political) topics. A higher proportion implies that the firm faces more severe political risk. The political risk measure for each firm in each month is based on the political risk value extracted from the most recent conference call.

3.2.2.3. Control variables

Our study focuses on the relation between firm-level political risk and delta-hedged option returns. Thus, to isolate the effect of political risk, we include in our main analysis a large set of alternative firm characteristics that reflect various aspects of a firm's performance or risk and have been used in prior studies on option return predictability (see, for example, Cao and Han 2013; Cao et al., 2021).

We first consider size, idiosyncratic volatility, reversal, momentum, book-to-market ratio, stock illiquidity, gross profitability, leverage and institutional ownership. These control variables are defined as follows. Size is the natural logarithm of the firm's market value (Banz, 1981). Book-to-market ratio is the book value of the firm's equity over the market value of the firm's equity (Fama and French, 1992). Reversal is the lagged one-month stock return (Jegadeesh, 1990). Momentum is the cumulative stock return over the last twelve months skipping the last month (Jegadeesh and Titman, 1993). Gross profitability is the firm's gross profit over total assets (Novy-Marx, 2013). Institutional ownership is the fraction of shares outstanding held by institutional investors (Nagel, 2005). Stock illiquidity is the ratio of the absolute value of the daily returns to the daily dollar trading volume, averaged over all days within the previous month (Amihud, 2002). Idiosyncratic volatility is the standard deviation of the residuals obtained from a regression of the daily stock returns on the Fama and French (1993) three factors over the previous month (Ang et al., 2006). We also control for leverage, defined as total debt over total assets (Campbell et al., 2008).

We further control for firm-level political sentiment to disentangle its effect from that of political risk. Political sentiment is the first moment effect of political exposure and is obtained from HHLT (2019), as well. The procedure for constructing $PSentiment$ closely follows that for measuring $PRisk$, i.e., it relies on counting the number of political bigrams conditioning on the proximity to words representing positive or negative sentiment based on the Loughran and McDonald (2011) sentiment dictionary, instead of words associated with risk or uncertainty. Controlling for political sentiment alleviates the concern that senior management might use politics as an excuse for negative news about economic performance.

To address potential concerns that the effect of firm-level political risk on delta-hedged option returns might simply pick up heterogeneous exposure to aggregate political risk, we also include a firm-level EPU beta. EPU beta is estimated from a regression of monthly stock excess returns on innovations of the economic policy uncertainty index controlling for market excess returns over the past 60 months with a requirement of at least 36 months of non-missing stock returns. We provide a detailed description of all the above variables in Appendix B1.

3.2.3. Descriptive statistics

Table 3.1 presents descriptive statistics for delta-hedged option returns, firm-level political risk, and other control variables during our sample period from January 2003 to June 2019. Following Gorbatikov et al. (2019), $PRisk$ is winsorized each month at (0, 95) and is normalized by its standard deviation across the whole sample. All explanatory variables (except for the dummy variables) are winsorized period-by-period at (0.5, 99.5) to mitigate the potential effects of outliers in our regression analysis.

[Insert Table 3.1 here]

After merging the option return with the political risk data, our final sample consists of 113,288 option-month observations for both delta-hedged call and put option returns and covers 3,450 unique firms. The average number of optionable stocks in our sample per month is 575. Table 3.1 shows that delta-hedged call and put option returns are negative on average (−1.19% and −0.77%, respectively), consistent with prior empirical studies (Bakshi and Kapadia, 2003b; Carr and Wu, 2009; Cao and Han, 2013). The average moneyness of call and put options is very close to 1 with a standard deviation of 0.05. The time to maturity ranges from 47 to 52 days, with an average of

50 days. Our variable of interest, $PRisk$, has an average value of 0.85 and a median value of 0.51 indicating a right-skewed distribution of political risk among firms in our sample.

Panel C of Table 3.1 reports the persistence of $PRisk$ at lags of one to seven quarters. The average cross-sectional correlation of $PRisk$ measured one quarter apart is 0.45. When measured at a lag of seven quarters, the average persistence of $PRisk$ drops to 0.27. Therefore, there is a high variation in firm-level political risk over time.

3.3. Effect of firm-level political risk on delta-hedged option returns

3.3.1. Cross-sectional regression analysis

We use Fama and MacBeth (1973) cross-sectional regressions to study the relation between firm-level political risk and future delta-hedged option returns. In particular, each month from January 2003 to May 2019, we perform the following cross-sectional regressions:

$$DepVar_{i,t+1} = \beta_0 + \beta_1 \times PRisk_{i,t} + \boldsymbol{\gamma}' \times \mathbf{Z}_{i,t} + \varepsilon_{i,t+1}\ , \tag{3.3}$$

where $DepVar_{i,t+1}$ is the call or put option return of firm i that is formed at the end of month t and is hedged on a daily basis until the end of month $t+1$, $PRisk_{i,t}$ is the level of political risk for firm i at the end of month t based on the most recent conference call, $\mathbf{Z}_{i,t}$ represents a vector of control variables that includes political sentiment, EPU beta, firm size, book-to-market ratio, return reversal, momentum, idiosyncratic volatility, Amihud measure of illiquidity, gross profitability, leverage, and institutional ownership, and $\varepsilon_{i,t+1}$ captures the error term.

Table 3.2 reports the time-series averages of the slope coefficients, the corresponding Newey and West (1987) t-statistics, and the average adjusted R^2 from 197 monthly cross-sectional regressions based on either univariate or multivariate models.

[Insert Table 3.2 here]

Specifications (1) and (3) present the results from the univariate analysis of call and put options, respectively. We observe that the coefficient on $PRisk$ is negative in both cases. A one standard deviation increase in political risk is associated with a decrease of 18 bps in one-month ahead delta-hedged call returns and a decrease of 15 bps in one-month ahead delta-hedged put returns. Moreover, these results are strongly significant at the 1% level (t-statistic = −7.12 for calls and t-statistic = −6.70 for puts). After adding the full set of control variables as in Specifications (2) and (4), the coefficient on $PRisk$ remains negative (−0.16 in both cases) with equally strong statistical significance. Therefore, the impact of other control variables on the association between firm-level political risk and future option returns is negligible. These results support the notion that political risk is priced in the equity option market. In other words, it appears that investors tend to pay a premium for options on firms with higher level of political risk, thus lowering their expected subsequent returns.

We note that the results with respect to the alternative firm characteristics are generally strong and confirm the predictions and findings of previous studies. For example, options with high idiosyncratic volatility and high stock illiquidity are associated with lower future returns, corroborating the idea that market makers charge a premium for options on stocks with high arbitrage costs (Cao and Han, 2013). Furthermore, in line with Cao and Han (2013) and Cao et al. (2021), delta-hedged option returns are positively associated with size, book-to-market, momentum, institutional ownership, and profitability.

We verify our cross-sectional regression results by using a panel regression analysis. We add time (i.e., monthly) fixed effects in all panel regression specifications as we are particularly interested in the cross-sectional effect of firm-level political risk. The estimation results are reported in Table B2.1 of Appendix B and are consistent with our main conclusion. For example, the coefficient on $PRisk$ is −0.17 (t-statistic = −7.45) for the multivariate regression with delta-hedged call option returns. Further adding industry fixed effects, defined by the two-digit SIC code, we observe that our coefficient of interest reduces to −0.13, but is still significant (t-statistic = −5.54).

Therefore, only 4 bps out of the 17-bps effect are driven by industry-level variation in political risk. If we further control for permanent differences across firms by adding firm-fixed effects, the coefficient on $PRisk$ drops to an effect size of 7 bps per standard deviation change but remains significant (t-statistic = -2.87). This is consistent with the idea that within-firm variation in political risk is also priced in option markets. We obtain very similar statistical inference from the panel regressions with delta-hedged put option returns.

To understand the mechanism that yields a negative predictive relation between firm-level political risk and option returns, we report in Table B2.2 the results from a contemporaneous regression between firm-level political risk and the difference between the option implied volatility (i.e., the actual option price) and the historical volatility of the underlying stock return (i.e., the theoretical option price). We find that firm-level political risk is positively correlated with IV$-$HV for both call and put options. This implies that investors are willing to pay high current option prices for high political risk firms and thus, earn lower subsequent option returns.

Collectively, the findings in this section suggest a strong negative association between firm-level political risk and future delta-hedged option returns. Equivalently, there is a premium for both call and put options on firms with high level of political risk. The relation remains robust after controlling for a large set of alternative firm characteristics.

3.3.2. Robustness analyses

3.3.2.1. Controlling for option-related characteristics

One might argue that the negative effect of firm-level political risk on future delta-hedged option returns just reflects the correction of some volatility-related option mispricing or volatility overreaction. Therefore, we start our analysis by controlling for two prominent option mispricing measures, i.e., volatility deviation and volatility term structure. Volatility deviation is the log difference between the past twelve month realized volatility and the current Black-Scholes implied volatility extracted from at-the-money (ATM) options (Goyal and Saretto, 2009). A larger (smaller) volatility deviation indicates an underestimation (overestimation) of volatility resulting in a higher (lower) future option return. Volatility term structure (VTS) is the difference between the long-term and the short-term implied volatility and could be related to investor sentiment where investors under- or overreact to current events (Vasquez, 2017).

[Insert Table 3.3 here]

Consistent with Goyal and Saretto (2009) and Vasquez (2017), Specifications (1) and (4) of Table 3.3 reveal a strong positive relation between the two volatility-related mispricing measures and future option returns, reflecting the correction of volatility mispricing over the next month. Importantly, the average slope coefficients on $PRisk$ show little change in magnitude when compared to Specifications (1) and (3) of Table 3.2. They remain negative at −0.17 (t-statistic = −6.90) and at −0.15 (t-statistic = −6.50) for the regression with delta-hedged call and put option returns, respectively. Therefore, the documented effect of political risk on the cross-section of option returns cannot be explained by standard volatility mispricing measures.

We further investigate whether volatility uncertainty, higher-order risk-neutral moments, jump risk, and option illiquidity can subsume the political risk effect. Volatility-of-volatility (VOV) is the standard deviation of the daily percentage changes in ATM implied volatility within the month (Baltussen et al., 2018; Cao et al., 2019). Risk-neutral skewness (RNS) and kurtosis (RNK) of stock returns are inferred from a portfolio of options across different strike prices following Bakshi et al. (2003). Volatility spread is the difference between the call option ATM implied volatility and the put option ATM implied volatility and proxies for jump risk (Bali and Hovakimian, 2009; Yan, 2011). Option illiquidity is measured as the option bid-ask spread divided by its midpoint price (Christoffersen et al., 2018; Cao et al., 2021). Consistent with the prior literature, Specifications (2), (3), (5) and (6) show that all the above variables exhibit significant predictive power for option returns. We further observe that the association between political risk and future call and put option returns remains particularly robust and always statistically significant at the 1% level.

Overall, we conclude that the $PRisk$ effect on the cross-section of option returns cannot be subsumed by various option-related characteristics.

3.3.2.2. Alternative measures of option returns

Next, we check the robustness of our findings to alternative definitions of option returns. Table 3.4 reports the results from Fama and MacBeth (1973) regressions of these alternative option return measures estimated over month $t+1$ on firm-level political risk controlling for a set of firm characteristics measured at the end of month t. The dependent variables in Specifications (1) to (3) of Table 3.4 include the delta-hedged call option gain until month end scaled by the initial stock price, the delta-hedged call option gain until month end scaled by the initial option price, and the delta-hedged call option gain until maturity scaled by the initial overall position, respectively. Specifications (4) to (6) utilize the same measures but for put options. We observe a consistently negative and strongly significant relation between these alternative option return measures and political risk.

[Insert Table 3.4 here]

Finally, in Specification (7) of Table 3.4 the dependent variable is the ex-post volatility risk premium (VRP), which is the difference between the ex-post realized volatility over month $t+1$ and the risk-neutral volatility calculated at the end of month t. This is motivated by the theoretical evidence in Bakshi and Kapadia (2003a), who show that within a stochastic volatility framework delta-hedged option returns are a monotonic transformation of the volatility risk premium. Consistent with our previous empirical evidence, political risk appears to be a strong negative predictor (t-statistic = −8.17) of the volatility risk premium too. Overall, our results lend strong support in favour of political risk affecting future option returns irrespective of the exact way these returns are estimated.

3.3.2.3. Portfolio-level analysis

The previous sections established a robust negative relation between firm-level political risk and subsequent option returns. However, several important questions remain unanswered: Is this relation monotonic? Is it driven equally by high- and low-political risk stocks? Does it hold throughout the sample period? And can it be explained by standard risk factors? To answer these questions, in this section we study the relation between political risk and option returns using a portfolio sorting approach. On the last trading day of each month from January 2003 to May 2019, we sort firms into quintiles based on their level of political risk. The top quintile contains the firms with the highest level of $PRisk$ and the bottom portfolio the firms with the lowest level of $PRisk$. We also construct a long-short portfolio that goes long options on high-$PRisk$ firms and short options on low-$PRisk$ firms. We rebalance the portfolios on a monthly basis and measure their returns. In total, we have 197 months of return data, starting from February 2003 to June 2019.

[Insert Table 3.5 here]

Table 3.5 reports the times series average of the delta-hedged call and put option returns across the five quintile portfolios as well as the Q5-Q1 portfolio. We find that the average option returns decline (almost) monotonically as we move from Q1 to Q5. In the case of call options, the low-$PRisk$ quintile has an average return of −0.97%, while the high-$PRisk$ quintile has an average return of −1.32%. Similarly, in the case of put options the low-$PRisk$ quintile has an average return of −0.56%, while the high-$PRisk$ quintile has an average return of −0.85%. Therefore, the results reveal a political risk premium of about 0.30% per month which is highly significant at the 1% level (t-statistic = −5.14 in the case of call options and t-statistic = −5.87 in the case of put options).[9] In addition, the largest drop in option returns is observed when we move from Q4 to Q5 (from −1.16% to −1.32% in the case of call options and from −0.71% to −0.85% in the case of puts options)

[9]Multiplying the difference in average $PRisk$ between the two quintile portfolios (1.62 – 0.07) with the Fama and MacBeth (1973) regression coefficients from the previous sections, we obtain similar economic significance. For example, using the coefficient from Specification (1) of Table 3.2 (–0.18), we obtain a premium of 0.28%.

and corresponds to the largest increase in the average level of $PRisk$ (from 0.59 to 1.62). We conclude that, while the effect of political risk on option returns is monotonic, it is mainly driven by firms with a high level of political risk. Finally, Figure 3.1 plots the monthly time-series of the Q5-Q1 portfolio returns across time. Strikingly, we observe that the returns are consistently negative across years for both call and put options. Therefore, the relation between firm-level political risk and option returns is not affected by specific subperiods.

We further examine whether the option return difference between high- and low-$PRisk$ firms can be explained by some prominent asset pricing factors. To this end, for each call and put option portfolio we report the alpha with respect to two factor models. The first model includes the Fama and French (1993) three factors augmented with the Carhart (1997) momentum factor. The second model further adds two volatility factors: the zero-beta straddle return of the S&P 500 index (Coval and Shumway, 2001), and the change in VIX (Ang et al., 2006). Table 3.5 shows that controlling for the above risk factors has minimal impact on our results. In fact, the Q5-Q1 alphas are always similar in magnitude and in statistical significance to the respective raw returns. Overall, the relation between $PRisk$ and future delta-hedged option returns is unlikely to be driven by firms' exposure to standard stock market or volatility risk factors.

3.4. Sources of return predictability

In this section, we examine three economic channels that might explain the negative relation between firm-level political risk and delta-hedged option returns: (1) option demand pressure, (2) information uncertainty, and (3) default risk.

3.4.1. Demand pressure

We posit that firm-level political risk can affect option prices primarily via a demand pressure channel. Bollen and Whaley (2004), Gârleanu et al. (2009) and Muravyev (2016) advocate that in an imperfect option market environment a higher demand for a specific class of options leads to higher options prices. The reason is that, as demand increases, market makers' positions grow larger and hence it becomes more difficult for them to perfectly hedge their inventory. This type of inventory risk forces risk-averse market makers to charge a higher premium. On their part, end-users willingly pay the elevated option prices because their demand pressure typically stems from their desire or necessity to engage into speculative or hedging trading strategies. Since political risk can potentially lead to financial shocks that cause price jumps or changes in volatility, it is natural to assume that investor demand – driven by both speculators and hedgers – for the options of politically risky firms is likely to be high. Consequently, we hypothesize that such a political risk-induced option demand pressure will lead to expensive option prices and low subsequent returns.

To test this hypothesis, we first investigate whether high firm-level political risk is indeed associated with increased option demand pressure. Option demand pressure is measured by the total number of option contracts open at the end of the month divided by the stock trading volume over the month.

[Insert Table 3.6 here]

Panel A of Table 3.6 reports the results from the cross-sectional regressions of option demand pressure on firm-level political risk controlling for the same set of characteristics that was considered in Table 3.2. We break down the option demand pressure into different option categories: (1) total calls, (2) out-of-the-money (OTM) calls, (3) in-the-money (ITM) calls, (4) total puts, (5) out-of-the-money (OTM) puts, and (6) in-the-money (ITM) puts.[10] It can be observed that firm-level political risk positively and significantly correlates with total call and put option demand pressure. The coefficients on $PRisk$ are 0.74 (t-statistic = 5.02) and 0.64 (t-statistic = 5.44), respectively. Furthermore, the relation is clearly more pronounced for OTM options than for ITM options. The evidence is consistent with the idea that investors increase their positions in calls and puts

[10] We obtain similar inference using option demand pressure defined as option trading volume over the month scaled by stock trading volume. The results are reported in Table B2.3 of Appendix B.

(especially OTM) of high-political risk firms because they wish to hedge against or speculate on potential political shocks.

To shed more light on the interrelations among firm-level political risk, option demand, and future delta-hedged option returns, we next examine whether the predictive power of political risk for option returns is more pronounced for options under higher demand pressure. To identify firms with high option demand pressure, each month, we define a dummy variable, $High\_Demand_{i,t}$, that takes the value of one if option demand of firm i is above the median option demand of all firms in that month, and zero otherwise. We then augment our baseline regression by adding this dummy variable and its interaction with firm-level political risk. The coefficient of interest is the one on the interaction term, as it measures how option demand pressure affects the relation between firm-level political risk and option returns.

Specification (1) in Panel B of Table 3.6 reports the result for delta-hedged call option returns, while Specification (2) reports the results for delta-hedged put option returns. In the case of call options, the coefficient on $PRisk$ is −0.06 (t-statistic = −1.64) implying a marginally significant relation between political risk and call option returns among low-demand options. In the case of put options, the respective coefficient is −0.09 (t-statistic = −3.36) implying a statistically strong relation even in the case of low-demand options. More importantly, the interaction term coefficient is negative and statistically significant at the 1% level (t-statistic = −3.84 for calls and t-statistic = −2.70 for puts) for both cases. In fact, the estimated interaction term coefficients reveal that the relation between political risk and call (put) option returns is four (two) times larger when we consider high-demand pressure options compared to low-demand pressure options. Collectively, in line with demand-based option pricing arguments (Bollen and Whaley 2004; Gârleanu et al., 2009), we provide evidence that political risk is more strongly associated with future option returns when it is accompanied by elevated demand on the part of end-users.

The above analysis relies on OptionMetrics data and hence exhibits two caveats. First, the data refer to unsigned trading volume. Therefore, one could argue that the increased option trading activity for high-political risk firms might be more seller- rather than buyer-initiated. Second, the data provide no information about the identity of the end-user initiating each trade. Ideally, we would like to obtain additional insights with respect to the way the demand pressure exerted by different types of investors is associated with the level of firm-level political risk. To address these two points, we perform an additional analysis that uses signed volume data from the International Securities Exchange (ISE) Trading Profile.[11,12] This dataset disaggregates all end-users' trades into buy or sell orders. It also classifies the trade initiator as a public customer or a firm. Customers can be either retails investors entering an option order through an online broker, or financial institutions and hedge funds trading through brokerage houses like Morgan Stanley or Goldman Sachs. In contrast, when firms such as Morgan Stanley or Goldman Sachs enter a trade for their own accounts, this is classified as a firm trade. While firms are typically considered the most sophisticated investors, Pan and Poteshman (2006) show that their trades do not have any predictive power for future stock returns probably because the option market is only used for hedging purposes by this investor group.[13] On the other hand, they find that the trades of public customers are the most informative for future stock returns indicating the presence of informed speculators in this group. We proceed by examining the relation between $PRisk$ and option net buying pressure – calculated as the difference between total monthly buy positions and sell positions scaled by stock trading volume (Bollen and Whaley, 2004) – across the two option investor groups and across different option categories.

[Insert Table 3.7 here]

The results from the cross-sectional regressions are reported in Table 3.7. Strikingly, we find that firm-level political risk is positively associated with call buying pressure from customers and

[11]While the ISE options volume data represent about 30% of the total equity options trading volume across all exchanges, Ge et al. (2016) show that the data are representative of the total options volume provided by OptionMetrics.

[12]Our analysis with the ISE options data covers the period from May 2005 to April 2016.

[13]Ge et al. (2016) suggest that firm proprietary traders have access to actual leverage while trading in the stock market and hence do not need to resort to the option market when they possess some private information.

put buying pressure from firms. The t-statistics are 2.79 for the former case and 2.14 for the latter case implying significance at the 1% and 5% level, respectively. In contrast, we do not observe any significant relation when we consider put buying pressure stemming from customers or call buying pressure stemming from firms. In line with the evidence presented in Table 3.6, we further find that the relation between political risk and customers' call buying pressure or firms' put buying pressure is mostly driven by OTM options.[14] Our evidence is in line with the idea that the increased buying pressure for the call options of high $PRisk$ firms reflects speculative demand on the part of retail investors or hedge funds, while the increased buying pressure for the put options of high $PRisk$ firms reflects hedging demand on the part of firm proprietary traders.

Overall, the above results provide novel insights with respect to how political risk is perceived by different investor groups (at least in the option market). In particular, firm proprietary traders – typically regarded as the most sophisticated group – tend to focus more on cases where political risk constitutes a threat and hence increase their put option positions in order to hedge against adverse price reactions. In contrast, public customers focus on the opportunities that political uncertainty may offer and speculate on potentially positive price jumps by purchasing call options. As an example of how political uncertainty can be related to both the downside and the upside, HHLT discuss the cases of two firms: one is an energy company that might be adversely affected by changes in emissions rules, while the second one is a high-tech firm that might benefit if the government decides to upgrade the telephone infrastructure of the Department of Defense. The evidence presented in Table 3.7 also sheds light on the reasons behind our return predictability results being equally strong for both call and put options, while one would probably expect political risk to be mostly associated with put option demand pressure. The answer hinges upon Pan and Poteshman's (2006) observation that public customers dominate the equity option market initiating about 70% of the total trading volume. Therefore, even if the average public customer

[14]In fact, the results for ITM call and put options are insignificant. The difference between this evidence and the evidence presented in Table 3.6, where political risk had a significant albeit economically weak effect on ITM options' demand pressure, is probably due to the smaller sample size.

trades much less than the average firm based on political risk considerations, collectively customers can have an equally strong effect on option prices.

3.4.2. Information uncertainty

Political risk has been shown to exacerbate the information asymmetries and frictions that already exist in the market. For example, when changes in governmental regulations or policies have heterogeneous impact across different geographical regions, the information sets of investors naturally differ (Aabo et al., 2016; Bradley et al., 2016). In addition, Chen et al. (2018) suggest that firms react to political uncertainty by reducing the quantity and quality of information disclosed. Finally, a series of recent studies (Ziobrowski et al., 2004; Gao and Huang, 2016; Christensen et al., 2017; Jagolinzer et al., 2020) show that certain market participants possess unique access to political information that they use to their benefit. It is conceivable that in the context of the option market such political risk-induced information uncertainties or asymmetries might translate to model risk – in the sense that market makers will have less confidence on their valuation models – and hence to a higher difficulty in dynamically hedging or replicating options (Figlewski, 1989; Green and Figlewski, 1999). In Green and Figlewski's (1999, pg. 1466) words, "…incorrectly estimated risk exposures may be greater than anticipated, and hedging strategies may be less effective than they are supposed to be." Hence, we expect that, in an opaque information environment, risk-averse market makers will require a higher compensation for supplying options on politically risky firms thus leading to lower delta-hedged option returns.

Following Zhang (2006), we use four proxies for information asymmetry or uncertainty. The first proxy is firm size, measured as the natural logarithm of the firm's market value at the end of the month. Smaller firms are more subject to information uncertainty. The second proxy is analyst coverage, measured as the number of analysts following the firm. Firms covered by more analysts are more likely to be associated with higher disclosure and more available information, which implies less uncertainty (Lang and Lundholm, 1996; Hong et al., 2000). The third proxy is dispersion in analyst earnings forecasts (DISP), measured as the standard deviation of analysts' earnings forecasts for the next fiscal year, scaled by the absolute value of the mean earnings forecast. Higher forecast dispersion implies higher uncertainty about future earnings and disagreement among analysts and market participants (Barron et al., 1998). The final proxy is cash flow volatility (CVOL), measured as the standard deviation of operating cash flows scaled by total assets over the past five years. Higher CVOL is likely associated with higher uncertainty about a firm's information and/or fundamentals.

Every month, we sort firms equally into low and high information uncertainty groups based on each of the above proxies. $High\_Uncertainty_{i,t}$ is a dummy variable that equals one for high information uncertainty firms – indicated by relatively smaller size, less analyst coverage, higher forecast dispersion, or greater cash flow volatility – and zero otherwise. We include this dummy variable and its interaction with firm-level political risk to our main cross-sectional regression specification to investigate our proposed channel.

[Insert Table 3.8 here]

Table 3.8 presents the results. Specifications (1)-(4) refer to call options returns, while Specifications (5)-(8) refer to put option returns. We see a consistent picture across all eight specifications that provides strong support to our hypothesis. In particular, the coefficients on the interaction term are negative and significant at the 1% level in all but one case (the specification with DISP when examining put option returns, where the interaction term is negative and significant at the 10% level). This means that although political risk affects the option returns even of those firms that have low information uncertainty – as shown by the almost universally significant coefficients on $PRisk$ – the effect is clearly stronger when we examine the group of high-information uncertainty firms. In fact, a one standard deviation increase in the $PRisk$ of high-information uncertainty firms is associated with an economically significant extra decrease of about 15 to 20 bps in future call and put option returns. Overall, our findings are consistent with the notion that firm-specific political risk affects option returns by exacerbating the information asymmetries that already exist among market participants. In other words, market makers have difficulty in processing with certainty the information related to political risks and hence demand a higher premium for continuing the supply of options.

3.4.3. Default risk

In the previous subsections, we investigated how political risk affects option returns through its impact on the demand and the supply side of the equity option market. Importantly, from an option valuation perspective the delta-hedged option returns encompass the volatility risk premium as well as higher-order risk premiums (Bakshi and Kapadia, 2003a; Bakshi and Madan, 2006). In a recent paper, Vasquez and Xiao (2020) show theoretically that firms with higher probability of default are rationally associated with lower future delta-hedged option returns because default risk makes the volatility premium more negative. In other words, investors are willing to accept more negative option returns in order to hedge against the adverse outcomes of elevated default risk. On a separate but related note, a burgeoning strand of the literature associates a firm's exposure to political shocks with its financial health and distress risk. For example, several studies demonstrate that uncertainties with respect to election results and policy changes can influence corporate decisions and alter a firm's financing, investing, or hiring plans and other activities (Julio and Yook, 2012; Gulen and Ion, 2016; Colak et al., 2017; Jens, 2017; Bhattacharya et al., 2017). Such uncertainties can diminish investment opportunities and adversely affect cash flows, thus threatening business continuity. Furthermore, political interference can significantly affect the value of assets on a firm's balance sheet. For example, political actions may result in the seizure of assets owned by US companies in a foreign country (Faccio et al, 2006; Tahoun and van Lent, 2019). In this respect, firms with high political risk are more likely to experience severe outcomes and default on their payments. Kaviani et al. (2020) provide empirical evidence linking policy uncertainty to increased probability of default. Motivated by the above two literatures, we advocate a complementary explanation for our findings, i.e., we hypothesize that political risk might affect option returns by enhancing the respective effect of default risk.[15] If this is indeed the case, we expect to find that the relation between political risk and future option returns is more pronounced (i.e., more negative) amongst firms with high default probability.

To proxy for default risk, we use the Merton's (1974) distance to default estimated as in Bharath and Shumway (2008). The detailed construction of this variable is described in Appendix B1. Each month, we sort firms equally into low and high default risk groups based on their probability of default. $High\_Default_{i,t}$ is a dummy variable that takes the value of one if default probability of firm i in month t is above the median default probability of all firms in month t, and zero otherwise. We add this dummy variable and its interaction with $PRisk_{i,t}$ to our baseline regression specification to examine our proposal.

[Insert Table 3.9 here]

Specifications (1) and (3) of Table 3.9 present the results for call and put options, respectively, without including any control variables, while Specifications (2) and (4) present the same results after controlling for our standard set of firm characteristics. First, we notice that the coefficient on $PRisk$ is negative and significant in all cases, implying that political risk leads to lower option returns even in the group of low default risk firms. More importantly, the interaction term, $PRisk \times High\ Default$, is negative and statistically significant at either the 1% or the 5% level across all four specifications meaning that the predictive power of political risk for option returns is markedly stronger among high-default risk firms. For example, Specifications (2) and (4) show that a one standard deviation increase in political risk is related to an extra 11-bps decrease in future call and put option returns when considering high-default risk firms (t-statistic = −2.32 for calls and t-statistic = −2.72 for puts). In fact, the absolute values of the interaction coefficients are as large as or even larger than the respective $PRisk$ coefficients implying that the effect size at

[15] In more technical terms, we posit that political risk might influence the jump intensity and/or jump size in Vasquez and Xiao's (2020) model.

least doubles. Overall, our empirical evidence provides support of the mechanism that links firm-level political risk and option returns through default risk.

3.5. Additional analyses on the $PRisk$ effect

3.5.1. The impact of lobbying and political donations

Several prior studies have shown that some firms attempt to alleviate their exposure to political shocks by establishing political connections or by engaging in political activism in the form of political donations and lobbying (Faccio, 2006; Cooper et al., 2010; Tahoun, 2014; Correia, 2014; Chen et al, 2015). Motivated by this strand of the literature, we hypothesize that option investors will accept less negative returns for the option contracts of politically active firms – or equivalently they will be willing to pay less for hedging or speculating through those contracts – because they will anticipate that the financial performance and the stock returns of such firms will be less sensitive to political risk. The purpose of conditioning the $PRisk$ effect on the level of political activism is twofold: First, it provides additional insights on the economic nature of the relation between political risk and option returns. Second, it serves as a validation exercise in the sense that a strong conditioning effect will mitigate potential concerns that the pricing impact of $PRisk$ just reflects some broad volatility risk that is priced in the context of the option market.

We examine firms' management of political exposure, either through lobbying politicians or by donating money to political campaigns using their Political Action Committees (PACs). Our source of data for lobby expenses and campaign contributions are from the Center for Responsive Politics (CRP).[16] We manually match company names in the CRP data with those in CRSP as they have no common identifier. Out of 3,450 unique firms in our sample, there are 1,395 lobbying firms and 764 firms that donate money to candidates during federal election campaigns.

We define $lnLobby$ as the natural logarithm of one plus a firm's lobbying expenses over the past four quarters and $lnDonate$ as the natural logarithm of one plus a firm's campaign donation

[16]The data is available at http://www.opensecrets.org.

amount over the past four quarters. We then interact both of these measures with firm-level political risk and include them in our baseline regression specification. The interaction term addresses the question of whether the effect of political risk on option returns is reduced in magnitude for firms that actively engage in the political process.

[Insert Table 3.10 here]

The regression results are presented in Table 3.10. In Specifications (1) and (4), we show that lobbying is associated with a less negative relation between political risk and future delta-hedged call and put option returns. The estimated coefficient on the interaction term is 0.57 (t-statistic = 1.84) and 0.68 (t-statistic = 2.85) for the regression with call and put option returns, respectively. We obtain a similar result by using campaign donations as a proxy for political activism in Specifications (2) and (5). The positive and significant interaction terms (1.14 with t-statistic = 3.28 for calls and 1.16 with t-statistic = 3.72 for puts) indicate a less prominent effect of political risk on option returns for donating firms. Overall, our evidence supports the idea that investors expect that politically active firms will be less affected by political shocks and hence accept a less negative return for a given level of $PRisk$.

We push our analysis one step further and investigate whether the mitigating role of political activism in the context of the political risk-option returns relation is affected by the firm's partisan or non-partisan donation strategy. For example, in 2020 the coal company Alliance Resource Partners collected around $1.3 million via PACs, but more than 99% of this amount was donated to candidates of the Republican party. This is consistent with the company having a history of opposing environmental regulations, such as the Clean Power Plan. Therefore, while Alliance Resource Partners is clearly a politically active firm, its partisan profile and its strong ties with the Republican party are likely to be regarded by investors as risk-enhancing rather than risk-mitigating elements. Overall, we expect that the dampening role of political activism that we document above is mainly driven by non-partisan firms, because such firms have access to the political decision-making process irrespective of which party is in power and in this manner are more able to protect themselves against adverse political shocks.

We identify firms that tilt their campaign donations towards only one particular party by defining $Partisan$, a dummy variable that is equal to one (zero) if the absolute difference between donations to Democratic and Republican political campaigns scaled by the total donation is above (below) the median value of all donating firms in a given month. In Specifications (3) and (6) of Table 10 we augment Specifications (2) and (5) by including the three-way interaction term $PRisk \times lnDonate \times Partisan$ and the associated lower-order terms into our baseline regression. The $PRisk \times lnDonate$ terms are positive in both specifications (1.82 with t-statistic = 3.30 for calls and 1.42 with t-statistic = 3.59 for puts) suggesting that political donations significantly reduce the extent to which political risk affects the option returns of non-partisan firms. This is in line with the idea that a more moderate donating approach serves indeed as a risk mitigation strategy. In addition, we find that in both specifications, the $PRisk \times lnDonate \times Partisan$ terms are negative and significant at the 10% level (−7.79 with t-statistic = −1.74 for calls and −5.95 with t-statistic = −1.70 for puts). Hence, for partisan firms the combined effect of political donations and political risk on option returns is even stronger. Overall, the results of this exercise lend support to the hypothesis that political contributions are perceived by option investors as a successful risk management strategy as long as they are not targeted to only one party.

3.5.2. Response to earning calls

The main analysis of the paper primarily focused on the cross-sectional relation between firm-level political risk and future option returns. To further strengthen our empirical evidence, we now turn to the investigation of the respective time-series relation by exploring how option returns behave before and after the release of new information about political risk during earnings conference calls.

Earnings calls constitute one of the main information sources that are utilized by investors in order to update their expectations about a firm’s future prospects and risk exposures. However, it is natural to assume that the level of political risk that is revealed during such calls is to some extent predictable and hence already incorporated into option prices. Therefore, we focus our attention to unexpected increases or decreases in political risk. Following Gorbatikov et al. (2019), we capture the surprise component of firm-level political risk using an AR1 regression augmented with the contemporaneous aggregate economy-wide political uncertainty (EPU) of Baker et al. (2016). In particular, we estimate the following regression separately for each firm using the full history of observations:

$$PRisk_t = \alpha + \beta \times PRisk_{t-1} + \gamma \times EPU_t + \varepsilon_t \,, \tag{3.4}$$

and define ε_t as the surprise component of firm-level political news during month t's earning call.[17]

[Insert Table 3.11 here]

Table 3.11 presents the average delta-hedged call and put option returns around unexpected increases or decreases in political risk. We define cases of an unexpected increase (decrease) in firm-level political risk as the earnings calls that correspond to the top (bottom) tercile of ε across the whole sample. To measure the impact of unexpected news about political risk on option returns, we compute the average option return in the two months before the earnings call month and compare it with the average option return in the two months after the earnings call month. The earnings call month is excluded from the analysis because its information content might be contaminated by other phenomena such as informed trading. If political risk is indeed priced by option investors, we expect to observe a significant time-series effect as well, i.e., we expect to find statistically different average option returns before and after the surprise event.

[17]To alleviate potential concerns that managers may inflate the discussion with respect to political risk in an attempt to camouflage poor recent performance or other types of bad news, we re-estimate Equation (4) controlling for stock return in month $t-1$ and firm profitability in month t. The results using this alternative estimation method for the unexpected change in political risk are quantitatively very similar and are presented in Table B2.4 of Appendix B.

We find that option returns decrease significantly after an unexpected increase in firm-level political risk. For example, the average delta-hedged put option return decreases from –0.66% to –0.78% after such an increase. Importantly, the spread between post-event and pre-event put option returns is negative (difference = –0.12%) and statistically significant (t-statistic = –2.21). We find a similar decreasing pattern for delta-hedged call option returns too. The difference between post-event and pre-event call option returns is –0.11% (t-statistic = –1.78). An opposite increasing pattern for option returns is observed after an unexpected decrease in political risk. However, this effect is not statistically significant. The difference in return spread between political risk increases and decreases is –0.17% (t-statistic = –2.13) for put option returns and –0.19% (t-statistic = –2.07) for call option returns, respectively.

Overall, our time-series empirical evidence lends further support to the idea that firm-level political risk is priced in the option market. Moreover, consistent with the cross-sectional analysis which showed that the $PRisk$ effect is mainly driven by high-political risk firms, the above analysis demonstrates that in a time-series context the $PRisk$ effect is mainly driven by increases in political risk. Intuitively, option investors willingly pay a high option premium in order to hedge against or speculate on unexpected news about political uncertainty. This high option premium gives rise to a more negative option return on average.

3.5.3. Topic-specific measures of political risk

In this last set of tests, we examine whether the political risk-option return relation is driven by specific political topics, and whether different topics affect option returns in different ways. HHLT (2019) apply the same textual analysis approach used for the construction of the overall political risk measure, but condition on words specific to a topic. Using training libraries of text on different political subjects, HHLT (2019) decompose $PRisk$ into eight separate aspects, including economic policy and budget, environment, trade, institutions and political process, healthcare, security and defense, tax policy, and technology and infrastructure. These measures capture the content of the conversation in the conference calls that is devoted to a particular political subject. We run the following cross-sectional regressions:

$$DepVar_{i,t+1} = \beta_0 + \beta_1 \times PRisk_{i,t}^{Topic} + \boldsymbol{\gamma}' \times \mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{3.8}$$

where $DepVar_{i,t+1}$ is the call or put option return of firm i in month $t+1$. $PRisk_{i,t}^{Topic}$ is one of the eight topic-specific measures of political risk for firm i at the end of month t based on the most recent conference call. All topic-based measures are winsorized each month at (0, 95) and are normalized to have unit standard deviation. $\mathbf{Z}_{i,t}$ represents the same vector of control variables that was used in Table 3.2.

[Insert Table 3.12 here]

Panel A of Table 3.12 presents the estimation results for delta-hedged call option returns and Panel B presents the respective results for delta-hedged put option returns. Both panels show that all topic-specific political risk measures exhibit strong negative predictive power for future option returns. We further observe that there is a large variation in the regression coefficients, with $PRisk^{Econ}$ having the least economically significant impact and $PRisk^{Health}$ having the most economically significant impact. Specifically, a one standard deviation increase in political risk related to healthcare translates to a decrease of 36 bps in next month's call option return and a decrease of 40 bps in next month's put option return. This effect size is more than three times larger than that of the economic-related political risk and more than two times larger than that of the overall political risk (see Table 3.2). This evidence is in line with considerable political uncertainty related to issues such as medical expenses reimbursement regulations affecting the profits of healthcare-related firms (Koijen et al., 2016). It could also be partially driven by the introduction of the Affordable Care Act (ACA) which spurred a series of political debates that span most of our sample period. In summary, we show that all aspects of political risk are priced in the option market and lead to more negative option returns. However, the magnitude of the pricing effect differs considerably across topics.

3.6. Conclusion

This essay investigates whether political risk is priced in the equity option market. Using a comprehensive text-based measure of firm-level political risk, we find a negative and highly significant cross-sectional relation between political risk and future delta-hedged call and put option returns. This relation remains robust when we control for a variety of stock- and option-related characteristics, as well as when we use alternative measures of option returns or topic-specific measures of political risk. A portfolio-sorting analysis suggests that option returns monotonically decrease in firm-level political risk, while the effect is more pronounced for firms with high political risk exposure and it persists throughout the whole sample period. The return spread between the two extreme political risk portfolios is about 0.30% per month and cannot be explained by standard equity risk or volatility risk factors.

We delve into the economic nature of the political risk effect by showing that, as expected, option returns are less sensitive to political risk when the company actively engages into the political process. We also find that political risk affects option prices and returns in a time-series context too. In particular, an unexpected increase in political risk after an earnings call leads to a significant decrease in the following months' option returns.

Finally, we show that the political risk effect is more pronounced among firms with high option demand pressure, high information uncertainty and high default risk. The former two findings are consistent with explanations that rely on demand and supply equilibrium effects, while the last finding points towards a rational incorporation of political risk into the stochastic discount factor. Importantly, we dissect the demand pressure arising from different investor groups. Our evidence demonstrates that firm-level political risk is associated with higher speculative call demand stemming from public customers and higher hedging put demand stemming from firm proprietary traders. It is possible that the two investor groups focus on different occurrences of political uncertainty or that they even perceive differently the same incidents. In any case, our evidence underlines the multifaceted nature of political risk at the individual stock level

Figure 3.1: Returns of long-short option portfolios across time
This figure plots the monthly time-series of the Q5-Q1 portfolio delta-hedged option returns (in percentage terms). Firms are sorted to portfolios on a monthly basis based on their level of political risk. The top panel presents the results for call options, while the bottom panel presents the results for put options. Our sample spans the period from January 2003 to June 2019.

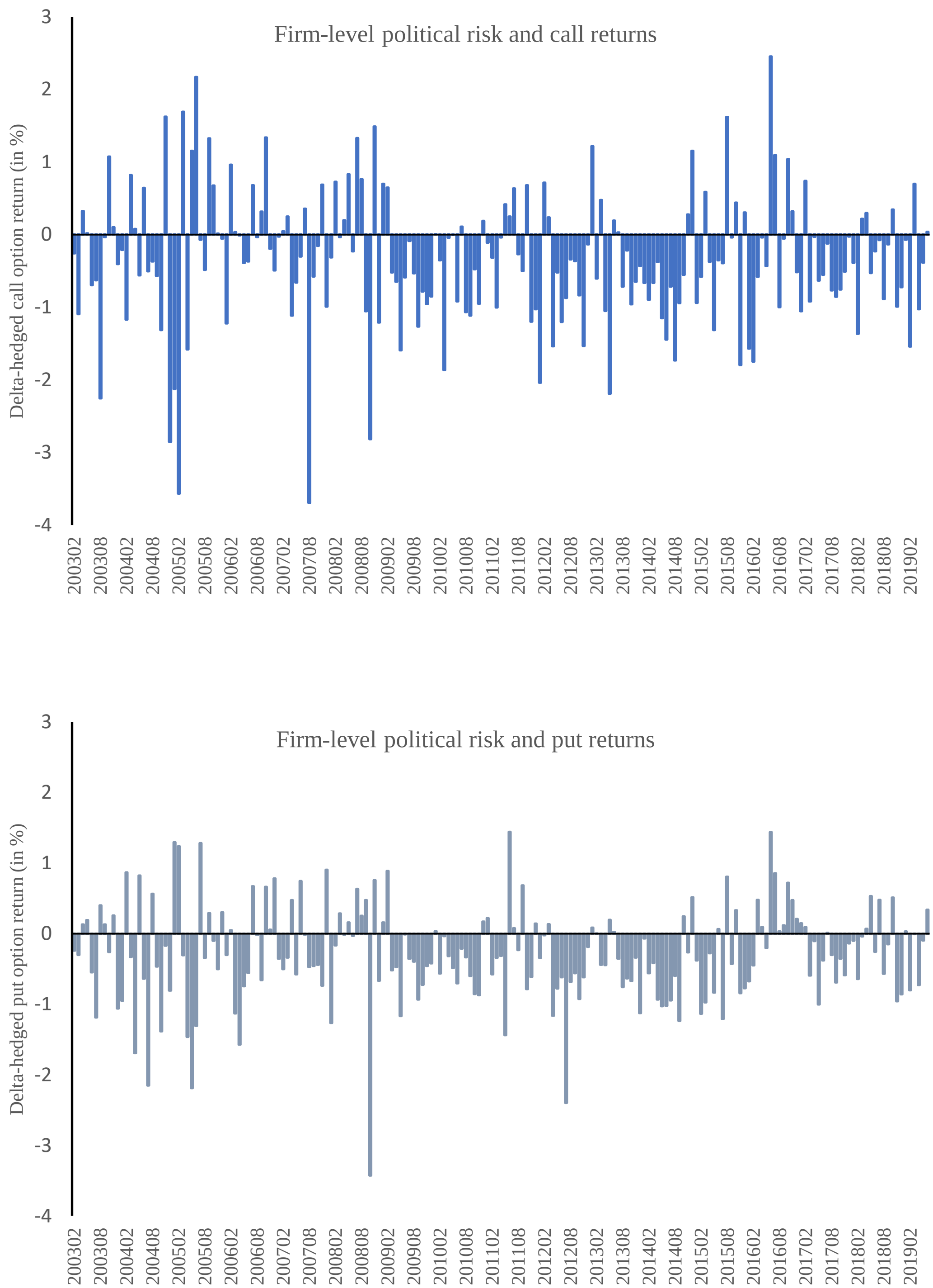

Table 3.1: Descriptive statistics

This table presents summary statistics for delta-hedged option returns, firm-level political risk, and control variables. All values are calculated as the time series average of the monthly cross-sectional means, distribution statistics, and percentiles. Panel A reports descriptive statistics for delta-hedged call (put) option returns, which are calculated as the scaled delta-hedged call (put) option gains. The delta-hedged call (put) option gain is the change over one month in the value of a portfolio that goes long one call (put) contract and is re-hedged daily with a certain number of underlying shares so that the portfolio is not sensitive to the underlying price movement. The scale factor for the delta-hedged call and put option gain is (△*S − C) and (P − △*S), respectively, where △ is the Black-Scholes option delta. Moneyness is the ratio of the underlying stock price to the option strike price. Panel B reports the text-based measure of firm-level political risk and the stock-related characteristics used in the paper. Panel C reports the time-series averages of the cross-sectional Pearson product-moment correlations between firm-level political risk measure in quarter t and firm-level political risk measured in quarter $t+\tau$ for $\tau \in \{1,2,3,4,5,6,7\}$. $PRisk$ and $PSentiment$ are standardized to have unit standard deviation. $PRisk$ is winsorized each month at (0, 95). All other variables are winsorized at (0.5, 99.5). Our sample spans the period from January 2003 to June 2019.

Panel A: Delta-hedged option returns

	Mean	STD	10th	25th	50th	75th	90th
Delta-hedged call gains till month-end / (Δ*S − C) (%)	−1.19	4.76	−4.73	−2.70	−1.23	0.12	1.88
Call moneyness	1.00	0.05	0.94	0.98	1.00	1.03	1.06
Delta-hedged put gains till month-end / (P − Δ*S) (%)	−0.77	3.85	−3.73	−1.94	−0.59	0.63	2.12
Put moneyness	1.00	0.05	0.94	0.98	1.00	1.03	1.07
Days to expiration	50	2	47	49	50	51	52

Panel B: Independent variables

	Mean	STD	10th	25th	50th	75th	90th
$PRisk$	0.85	0.94	0.04	0.18	0.51	1.14	2.23
$PSentiment$	1.01	0.91	0.03	0.49	0.96	1.50	2.07
EPU beta	−0.06	0.57	−0.70	−0.37	−0.07	0.24	0.58
Size	14.91	1.47	13.12	13.85	14.77	15.87	16.93
BM	0.47	0.39	0.12	0.21	0.36	0.61	0.92
IdioVol	0.28	0.15	0.13	0.17	0.24	0.34	0.47
Reversal	0.01	0.08	−0.09	−0.04	0.01	0.06	0.11
Momentum	0.22	0.51	−0.27	−0.08	0.13	0.39	0.77
Illiquidity	0.20	0.66	0.01	0.02	0.05	0.16	0.44
Inst Own	0.78	0.23	0.44	0.68	0.83	0.93	1.01
Leverage	0.53	0.26	0.20	0.34	0.52	0.70	0.87
Profitability	0.33	0.29	0.05	0.16	0.30	0.47	0.70

Panel C: Average persistence of $PRisk$ (at the quarterly frequency)

ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7
0.45	0.35	0.32	0.31	0.29	0.28	0.27

Table 3.2: The effect of firm-level political risk on delta-hedged option returns: Fama-MacBeth regressions
This table reports the average coefficients and average adjusted R^2 values from Fama and MacBeth (1973) cross-sectional regressions of delta-hedged option returns in month $t+1$ (in percentage terms) on firm-level political risk ($PRisk$) and control variables measured at the end of month t. The main independent variable is the standardized $PRisk$ at the end of month t based on the most recent conference call. Control variables include political sentiment, EPU beta, log of market cap, book-to-market ratio, idiosyncratic volatility, return reversal, momentum, stock illiquidity, institutional ownership, leverage, and gross profitability. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns		Delta-hedged put option returns	
	(1)	(2)	(3)	(4)
$PRisk$	−0.18***	−0.16***	−0.15***	−0.16***
	(−7.12)	(−6.58)	(−6.70)	(−7.73)
$PSentiment$		−0.02		−0.02
		(−1.20)		(−1.26)
EPU beta		0.03		0.02
		(0.81)		(0.48)
Size		0.20***		0.18***
		(9.92)		(13.17)
BM		0.31***		0.32***
		(4.56)		(6.28)
IdioVol		−2.02***		−1.73***
		(−14.35)		(−18.53)
Reversal		0.96***		−0.07
		(3.69)		(−0.31)
Momentum		0.18**		0.11**
		(2.08)		(2.20)
Illiquidity		−0.27***		−0.29***
		(−4.71)		(−7.28)
Inst		0.48***		0.45***
		(5.26)		(5.11)
Leverage		0.10		0.14**
		(1.22)		(2.27)
Profitability		0.54***		0.37***
		(6.36)		(4.57)
Intercept	−1.16***	−4.32***	−0.60***	−3.41***
	(−11.05)	(−11.62)	(−4.71)	(−12.82)
Adjusted R^2	0.001	0.086	0.001	0.092

Table 3.3: Controlling for option-related characteristics

This table reports the Fama and MacBeth (1973) cross-sectional regression results for the effect of firm-level political risk on delta-hedged option returns controlling for several option-related characteristics. The dependent variable is the delta-hedged call or put option return in month $t+1$ (in percentage terms). The main independent variable is the standardized firm-level political risk ($PRisk$) at the end of month t based on the most recent conference call. Volatility deviation is the log difference between the past twelve month realized volatility and the current Black-Scholes implied volatility extracted from ATM options. Volatility term structure (VTS) is the difference between long-term and short-term implied volatility. Risk-neutral skewness (RNS) and kurtosis (RNK) of stock returns are inferred from a portfolio of options across different strike prices following Bakshi et al. (2003). Volatility spread is the difference in the implied volatilities between ATM call and ATM put options at the month end. Volatility-of-volatility (VOV) is the standard deviation of the daily percentage change in ATM implied volatility within the month. Option illiquidity is the option bid-ask spread divided by its midpoint price. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns			Delta-hedged put option returns		
	(1)	(2)	(3)	(4)	(5)	(6)
$PRisk$	−0.17***	−0.18***	−0.17***	−0.15***	−0.15***	−0.14***
	(−6.90)	(−6.70)	(−6.88)	(−6.50)	(−6.76)	(−6.39)
Volatility Deviation	1.87***	1.77***	1.70***	1.64***	1.49***	1.40***
	(12.64)	(12.00)	(11.39)	(13.94)	(14.18)	(13.91)
VTS	2.48***	1.87***	1.73***	3.23***	2.97***	2.75***
	(4.48)	(3.47)	(3.29)	(5.67)	(5.72)	(5.58)
RNS		−0.61***	−0.52***		−0.25***	−0.14***
		(−11.99)	(−9.64)		(−4.74)	(−3.66)
RNK		0.18***	0.22***		0.18***	0.25***
		(7.16)	(7.96)		(7.59)	(10.08)
Volatility Spread		−4.18***	−4.57***		11.40***	11.19***
		(−6.87)	(−7.49)		(18.29)	(18.73)
VOV		−6.49***	−5.34***		−5.46***	−3.83***
		(−9.40)	(−7.07)		(−8.93)	(−6.16)
Option Illiquidity			−1.52***			−2.23***
			(−7.55)			(−11.26)
Intercept	−1.18***	−1.85***	−1.84***	−0.62***	−1.10***	−1.11***
	(−8.64)	(−9.46)	(−9.18)	(−3.92)	(−6.36)	(−6.20)
Adjusted R^2	0.03	0.06	0.08	0.03	0.09	0.11

Table 3.4: Alternative dependent variables

This table presents the Fama and MacBeth (1973) cross-sectional regression results for the effect of firm-level political risk on different measures of delta-hedged option returns: (1) delta-hedged gain until month end / stock price, (2) delta-hedged gain until month end / option price, (3) delta-hedged gain until maturity / initial overall position, and (4) ex-post volatility risk premium defined as the difference between the realized volatility of month t+1 and the risk-neutral volatility estimated at the end of month t. The main independent variable is the standardized firm-level political risk ($PRisk$) at the end of month t based on the most recent conference call. The control variables included are the same with Specification (2) of Table 3.2. We report only the coefficient on $PRisk$; the coefficients on the remaining variables are suppressed for the sake of brevity. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Call Options			Put Options			
	(1) Gain till month end/ Stock Price	(2) Gain till month end/ Option Price	(3) Gain till maturity/ (Δ*S − C)	(4) Gain till month end/ Stock Price	(5) Gain till month end/ Option Price	(6) Gain till maturity/ (P − Δ*S)	(7) VRP
$PRisk$	−0.04***	−0.54***	−0.13***	−0.07***	−1.07***	−0.16***	0.50***
	(−5.44)	(−3.24)	(−6.63)	(−7.22)	(−4.55)	(−8.55)	(−8.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.07	0.03	0.07	0.10	0.04	0.09	0.14

Table 3.5: Portfolio-sorting analysis

This table reports the average returns (in percentage terms) of option portfolios sorted by the underlying asset's $PRisk$. $PRisk$ is the standardized firm-level political risk at the end of month t based on the most recent conference call. At the end of each month from January 2003 to May 2019, we sort stocks into quintiles according to their political risk level. We report the average next month's delta-hedged call and put option portfolio return for each equal-weighted quintile and the average return differential between the top and the bottom quintile. We also report the alphas with respect to two factor models. The first model includes the Fama and French (1993) three factors and the Carhart (1997) momentum factor, while the second model further adds the zero-beta straddle return of the S&P 500 index from Coval and Shumway (2001) and the change in VIX. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

		Delta-hedged call option returns (%)			Delta-hedged put option returns (%)		
	Average $PRisk$	Return	4-factor alpha	6-factor alpha	Return	4-factor alpha	6-factor alpha
Q1	0.07	−0.97	−0.91	−0.96	−0.56	−0.47	−0.41
		(−8.48)	(−7.40)	(−8.04)	(−5.47)	(−4.14)	(−3.67)
Q2	0.18	−1.02	−0.96	−0.98	−0.66	−0.57	−0.50
		(−10.20)	(−9.97)	(−10.25)	(−6.11)	(−4.88)	(−4.68)
Q3	0.33	−1.07	−1.00	−1.05	−0.72	−0.65	−0.59
		(−9.89)	(−9.43)	(−9.57)	(−6.84)	(−5.85)	(−5.52)
Q4	0.59	−1.16	−1.10	−1.12	−0.71	−0.63	−0.56
		(−11.21)	(−11.08)	(−11.00)	(−6.77)	(−5.63)	(−5.04)
Q5	1.62	−1.32	−1.24	−1.27	−0.85	−0.76	−0.68
		(−11.79)	(−11.82)	(−11.35)	(−7.70)	(−6.81)	(−6.82)
Q5−Q1	1.55	−0.34***	−0.34***	−0.31***	−0.29***	−0.30***	−0.28***
		(−5.14)	(−5.02)	(−4.71)	(−5.87)	(−5.53)	(−5.26)

Table 3.6: Firm-level political risk and option demand pressure

Panel A reports the results from Fama and MacBeth (1973) cross-sectional regressions of option demand pressure on $PRisk$, controlling for several firm characteristics. Option demand pressure is measured as the total number of option contracts open at the end of the month divided by the stock trading volume over the month. Option demand pressure is divided into six categories: (1) total calls, (2) OTM calls, (3) ITM calls, (4) total puts, (5) OTM puts, and (6) ITM puts. Panel B presents the Fama and MacBeth (1973) cross-sectional regression results with respect to the effect of option demand pressure on the relation between firm-level political risk and delta-hedged option returns. $High\ Demand_{i,t}$ is a dummy variable that takes the value of one if the option demand pressure of the firm is above the median option demand pressure in that month and zero otherwise. The control variables included are the same with Specification (2) of Table 3.2. We report only the coefficients on $PRisk$, $High\_Demand$, and their interaction; the coefficients on the remaining variables are suppressed for the sake of brevity. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: $PRisk$ and option demand

	Total Calls	OTM Calls	ITM Calls	Total Puts	OTM Puts	ITM Puts
$PRisk$	0.74***	0.49***	0.25***	0.64***	0.48***	0.15***
	(5.02)	(4.86)	(4.53)	(5.44)	(5.94)	(3.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.11	0.10	0.15	0.08	0.10	0.12

Panel B: Conditioning effect of option demand pressure

	Delta-hedged call option returns	Delta-hedged put option returns
	(1)	(2)
$PRisk$	−0.06	−0.09***
	(−1.64)	(−3.36)
$PRisk \times High\_Demand$	−0.18***	−0.10***
	(−3.84)	(−2.70)
$High\_Demand$	−0.13***	−0.26***
	(−4.20)	(−8.39)
Controls	Yes	Yes
Adjusted R^2	0.09	0.10

Table 3.7: Firm-level political risk and net buying pressure for different investor groups

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of option net buying pressure on $PRisk$, controlling for several firm characteristics. Net buying pressure is the difference between the total monthly buy positions (open buy plus close buy) and sell positions (open sell plus close sell) scaled by stock trading volume in that month. Net buying pressure is divided into six categories: (1) total calls, (2) OTM calls, (3) ITM calls, (4) total puts, (5) OTM puts, and (6) ITM puts. Panel A shows the results for public customers and Panel B shows the results for firm proprietary traders. The control variables included are the same with Specification (2) of Table 3.2. We report the coefficients on $PRisk$; the coefficients on control variables are suppressed for the sake of brevity. The data are from the International Securities Exchange and cover the period from May 2005 to April 2016. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Public customers

	Total Calls	OTM Calls	ITM Calls	Total Puts	OTM Puts	ITM Puts
$PRisk$	1.33***	0.97**	0.35	−0.22	−0.50	0.24
	(2.79)	(2.25)	(0.98)	(−0.58)	(−1.45)	(1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.02	0.02	0.02	0.01	0.01	0.01

Panel B: Firm proprietary traders

	Total Calls	OTM Calls	ITM Calls	Total Puts	OTM Puts	ITM Puts
$PRisk$	0.01	−0.12	0.12	0.90**	1.04**	−0.05
	(0.03)	(−0.54)	(0.80)	(2.14)	(2.53)	(−0.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.01	0.01	0.00	0.01	0.01	0.01

Table 3.8: Firm-level political risk and information uncertainty

This table presents the Fama and MacBeth (1973) cross-sectional regression results with respect to the effect of information uncertainty on the relation between firm-level political risk and delta-hedged option returns. We sort firms into low and high information uncertainty groups based on different proxies: (1) market cap, (2) analyst coverage, (3) dispersion in analyst earnings forecast, and (4) cash flow volatility. $High\_Uncertainty_{i,t}$ is a dummy variable that equals one for high information uncertainty firms, which are indicated by relatively smaller size, less analyst coverage, higher forecast dispersion, and greater cash flow volatility. The control variables included are the same with Specification (2) of Table 3.2. We report only the coefficients on $PRisk$, $High\_Uncertainty$, and their interaction; the coefficients on the remaining variables are suppressed for the sake of brevity. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns				Delta-hedged put option returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proxy for High Uncertainty	Size	Analyst Coverage	Analyst DISP	CVOL	Size	Analyst Coverage	Analyst DISP	CVOL
$PRisk$	–0.02	–0.07**	–0.09***	–0.09***	–0.05**	–0.09***	–0.13***	–0.07***
	(–0.88)	(–2.27)	(–2.97)	(–3.48)	(–2.02)	(–3.82)	(–4.72)	(–3.07)
$PRisk * High\_Uncertainty$	–0.26***	–0.19***	–0.14***	–0.16***	–0.20***	–0.15***	–0.07*	–0.19***
	(–5.60)	(–4.18)	(–3.05)	(–3.64)	(–5.21)	(–4.51)	(–1.82)	(–4.55)
$High\_Uncertainty$	–0.27***	0.06**	0.01	–0.13***	–0.28***	0.02	0.01	–0.05**
	(–5.47)	(2.14)	(0.26)	(–3.21)	(–7.72)	(0.90)	(0.31)	(–2.02)
Controls	Yes(*)	Yes	Yes	Yes	Yes(*)	Yes	Yes	Yes
Adjusted R^2	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09

(*) Excludes Size

Table 3.9: Firm-level political risk and default risk

This table presents the Fama and MacBeth (1973) cross-sectional regression results with respect to the effect of default risk on the relation between firm-level political risk and delta-hedged option returns. Default risk is measured as the probability of default using Bharath and Shumway's (2008) version of the Merton distance to default model. $High\_Default_{i,t}$ is a dummy variable that takes the value of one if the firm's default risk is above the median default risk in that month and zero otherwise. The control variables included are the same with Specification (2) of Table 3.2. We report only the coefficients on $PRisk$, $High\_Default$, and their interaction; the coefficients on the remaining variables are suppressed for the sake of brevity. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns		Delta-hedged put option returns	
	(1)	(2)	(3)	(4)
$PRisk$	−0.10**	−0.11***	−0.08**	−0.11***
	(−2.51)	(−3.22)	(−2.44)	(−3.50)
$PRisk \times High\_Default$	−0.17***	−0.11**	−0.16***	−0.11***
	(−3.17)	(−2.32)	(−4.01)	(−2.72)
$High\_Default$	−0.52***	−0.11**	−0.39***	−0.03
	(−9.02)	(−2.50)	(−9.62)	(−0.88)
Controls	No	Yes	No	Yes
Adjusted R^2	0.02	0.09	0.02	0.09

Table 3.10: Firm-level political risk and political risk management

This table presents the Fama and MacBeth (1973) cross-sectional regression results with respect to the effect of political activism on the relation between firm-level political risk and delta-hedged option returns. $lnLobby$ is the natural logarithm of one plus a firm's lobbying expense over the past four quarters. $lnDonate$ is the natural logarithm of one plus a firm's campaign donation over the past four quarters. $Partisan$ is a dummy variable that takes the value of one if the absolute difference between donations to Democratic and Republican political campaigns scaled by the total donation is above the median across firms in that month. The control variables included are the same with Specification (2) of Table 3.2. We report only the coefficients on $PRisk$, $lnLobby$, $lnDonate$, $Partisan$, and their associated interactions; the coefficients on the remaining variables are suppressed for the sake of brevity. The coefficients on $lnLobby$ and $lnDonate$, as well as the associated interaction terms, have been multiplied by 100. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call returns			Delta-hedged put returns		
	(1)	(2)	(3)	(4)	(5)	(6)
$PRisk$	−0.20***	−0.20***	−0.20***	−0.20***	−0.19***	−0.19***
	(−5.65)	(−6.86)	(−6.98)	(−6.76)	(−7.25)	(−7.33)
$PRisk \times lnLobby$	0.57*			0.68***		
	(1.84)			(2.85)		
$lnLobby$	−0.80***			−0.84***		
	(−3.54)			(−5.58)		
$PRisk \times lnDonate$		1.14***	1.82***		1.16***	1.42***
		(3.28)	(3.30)		(3.72)	(3.59)
$lnDonate$		−1.04***	−1.83***		−0.84***	−1.31***
		(−3.33)	(−5.08)		(−4.68)	(−4.53)
$Partisan$			−0.09			0.17
			(−0.37)			(0.58)
$PRisk \times Partisan$			0.67			0.58
			(1.39)			(1.64)
$lnDonate \times Partisan$			2.43			−0.89
			(1.07)			(−0.34)
$PRisk \times lnDonate \times Partisan$			−7.79*			−5.95*
			(−1.74)			(−1.70)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.09	0.08	0.09	0.09	0.09

Table 3.11: Response to earnings calls

This table reports the average monthly delta-hedged call and put option returns (in percentage terms) around unexpected increases and decreases in firm-level political risk. The surprise component for each firm's political risk is captured using an AR1 regression augmented with the contemporaneous EPU value. We define unexpected increases (decreases) in firm-level political risk as the earnings calls that correspond to the top (bottom) tercile of this surprise component across the whole sample. We report the average delta-hedged option returns in the two months before and the two months after the earnings call month. Our sample spans the period from January 2003 to June 2019. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns			Delta-hedged put option returns		
Political risk surprise	Increase	Decrease	Difference	Increase	Decrease	Difference
Pre-event return	−0.94	−0.97	0.03	−0.66	−0.75	0.08
Post-event return	−1.05	−0.89	−0.16	−0.78	−0.70	−0.08
Difference	−0.11*	0.08	−0.19**	−0.12**	0.05	−0.17**
	(−1.78)	(1.23)	(−2.07)	(−2.21)	(0.80)	(−2.13)

Table 3.12: Topic-specific measures of political risk and delta-hedged option returns
This table reports the Fama and MacBeth (1973) cross-sectional regression results for the effect of different topic-specific political risks on delta-hedged option returns. The dependent variable is the delta-hedged call (Panel A) or put (Panel B) option return in month $t+1$ (in percentage terms). The overall measure of political risk is decomposed into eight separate topics, including economic policy and budget, environment, trade, institutions and political process, healthcare, security and defence, tax policy, technology and infrastructure. All topic-based measures are winsorized each month at (0, 95) and are standardized to have unit standard deviation. The control variables included are the same with Specification (2) of Table 3.2. We report only the coefficients on the topic-based political risk measures; the coefficients on the remaining variables are suppressed for the sake of brevity. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Delta-hedged call option returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PRisk^{Econ}$	−0.10***							
	(−3.76)							
$PRisk^{Envi}$		−0.14***						
		(−3.62)						
$PRisk^{Trade}$			−0.11**					
			(−2.42)					
$PRisk^{Inst}$				−0.19***				
				(−5.48)				
$PRisk^{Health}$					−0.36***			
					(−5.94)			
$PRisk^{Security}$						−0.16***		
						(−5.15)		
$PRisk^{Tax}$							−0.12***	
							(−3.07)	
$PRisk^{Tech}$								−0.13***
								(−3.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Panel B: Delta-hedged put option returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PRisk^{Econ}$	−0.13***							
	(−5.01)							
$PRisk^{Envi}$		−0.16***						
		(−4.41)						
$PRisk^{Trade}$			−0.16***					
			(−3.78)					
$PRisk^{Inst}$				−0.23***				
				(−6.91)				
$PRisk^{Health}$					−0.40***			
					(−7.83)			
$PRisk^{Security}$						−0.19***		

						(−6.33)		
$PRisk^{Tax}$							−0.14***	
							(−3.98)	
$PRisk^{Tech}$								−0.16***
								(−5.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Chapter 4

Climate sensitivity and mutual fund performance

4.1. Introduction

Climate change has been one of the most pressing issues of our era, posting substantial risks for investors' portfolio companies. Such risks to portfolio companies can come from their exposure to natural disaster, regulatory climate policies, and technological innovations (Krueger et al., 2020; Hong et al., 2020). Given the highly uncertain trajectory and economic consequences of climate change, investors increasingly find it desirable to hedge themselves against the realizations of climate risk (Engle et al., 2020). Despite the challenge, this practice can potentially be done by investing into stocks with lower exposure to climate risk, e.g., stocks of firms with high E-Scores.[1] Such trend to sustainable investing raises an important question of whether investors that effectively hedge against climate risk outperform the otherwise similar investors. The answer to this question can facilitate financial flows into climate-hedging portfolios and hence, support mitigation of climate change.

[1]Engle et al. (2020) show that stocks of firms with higher E-Scores (Environmental Scores), which are collected from KLD and Sustainalytics database, have higher returns during periods with negative news about the future path of climate change.

In this chapter, we study the above question in the context of active equity mutual funds. We focus on mutual funds for several reasons. First, as the largest group of institutional investors, mutual funds are set up with the explicit intention to meet the demand of integrating sustainability criteria into their investment processes (Bauer et al., 2005). Second, active mutual funds are directly exposed to climate risk through their holdings of assets that might increase (or decrease) in value when climate concerns elevate. In this respect, we capture a mutual fund's sensitivity to climate change news risk, i.e., climate beta, as its return covariance with innovations in the market-wide negative climate change news index developed by Engle et al. (2020). This measure of climate change risk captures negative news (or concerns) on various climate risk topics, including extreme weather events, physical changes to the planet, regulatory risks, and the price of fossil fuels. Hence, a positive (negative) climate beta implies an increase (decrease) in the mutual fund's return during heightened aggregate climate change concern.

Climate beta directly reflects the ability of funds to hedge against climate change concern and might contain different information from other proxies of green (or sustainable) funds that are based on carbon emission or ESG (Environmental, Social, Governance) rating data. For example, if besides carbon emission level, the market also values other aspects such as green innovation, environmental technology, climate strategy, environmental management systems, etc., mutual funds holding equities with these characteristics would benefit when climate concerns heighten. A recent study by Cohen et al. (2020) documents a striking disconnect that incremental green patent is more likely to come from energy and more poorly scored ESG firms. Another problem inherited in the use of carbon emission and ESG data to measure a fund greenness is that carbon emission information is voluntarily disclosed and is thus limited in terms of cross-sectional coverage, while ESG scores are estimated with a great disagreement among different data providers (see Chatterji et al., 2016; Berg et al., 2020). Encompassing these issues, our market-based measure of climate beta clearly distinguishes which funds are expected to gain or lose from a shift in climate concern.

In examining the association between climate beta and future mutual fund performance, two hypotheses compete. On the one hand, mutual funds whose returns negatively covary with climate change risk (i.e., high exposure to climate risk) must be compensated in terms of higher expected returns. Such funds lose value during heightened climate change concern – a state of the world that investors dislike, so they are exposed to higher risk and demand higher expected returns. The otherwise similar funds accept lower expected returns for their hedging purpose. This is in the spirit of Fama and French (2007) and Pastor et al. (2021) that if investors prefer green firms, the expected returns from investing in companies that are greener will be lower in equilibrium. With a similar argument, as long as agents care about climate change, ones who tilt their portfolios toward climate-hedging assets might accept below-market expected returns in exchange for satisfying their stronger tastes. This hypothesizes a negative relation between climate beta and mutual fund performance.

On the other hand, it is possible that market prices have still been adjusting to an equilibrium that reflects increasing climate change consideration. Pastor et al. (2021) derive a wedge between expected and realized returns for sustainable investing. Green assets perform better than expected when environmental concerns strengthen unexpectedly via either investor channel (i.e., demands for sustainable holdings) or customer channel (i.e., demands for sustainable products). During the transition period, i.e., in the past two decades, rising investors' preference for climate-friendly stocks could push up their relative market prices over time (Cornell, 2021), and investors holding these stocks could earn superior risk-adjusted returns. Furthermore, firms investing to mitigate climate change can build social capital, trust, and consumers' awareness that might enhance profitability and firm valuation (see Servaes and Tamayo (2017) for a review). Therefore, stocks of firms that hedge against climate change could experience investor-driven price pressure and/or have stronger financial fundamentals, which in turn boost the subsequent performance of mutual funds that tilt their portfolios toward such stocks and hedge against climate change.

Our empirical analysis provides strong support for the positive relation between climate sensitivity and mutual fund performance. The relation is both economically and statistically significant based on a sample of 2,781 actively managed equity mutual funds over the period from July 2008 to June 2018. To capture fluctuations in climate concern, we use the monthly Crimson Hexagon

(CH)'s negative sentiment climate change news index, which is a text-based marketwide measure reflecting negative climate risk news and being constructed by Engle et al. (2020). For each fund-month, we run a time-series regression of mutual fund excess returns over the past 24 months on innovations in the climate change news index while controlling for standard risk exposures. The regression coefficient on the climate risk innovations captures the fund's climate beta. We sort mutual funds based on their climate betas, group them into quintiles, and examine the average returns of these quintiles over the next one month. We find that the highest climate beta quintile on average outperforms the lowest climate beta quintile by 0.21% (t-statistic = 3.14) in the next month. The risk-adjusted return difference between these two extreme quintiles remains significant after controlling for standard risk factors in the asset pricing literature.

We examine the robustness of our findings. First, we confirm the positive relation between climate beta and subsequent mutual fund performance in Fama and MacBeth (1973) regressions controlling for various fund characteristics and fund styles. Second, our inference is robust to alternative measures of climate change concern, including Wall Street Journal (WSJ) climate change news index developed by Engle et al. (2020) and Internet search volume intensity on topic "climate change" constructed by Google Trends. Using longer time series of climate change index such as WSJ news index, we show that the positive relation between climate beta and mutual fund performance is only pronounced during post–2000 period when investors pay more attention for climate issues. Finally, our results hold for value-weighted portfolios and apply to both gross-of-fee and net-of-fee returns, and the predictive power of climate beta for mutual fund returns extends as far as 5 months into the future.

A possible explanation for the above findings is that positive climate beta funds tilt their holdings toward positive climate beta stocks and such climate-hedging stocks earn higher excess returns because of facing greater demand-driven price pressure and/or having superior financial performance over the recent period. To test this hypothesis, we examine whether there is a positive relation between stock-level climate betas and subsequent stock returns, which factors drive this relation, and whether high climate beta funds outperform by simply holding (tilting their portfolios toward) high climate beta stocks.

Similar to computing fund-level climate beta for each fund-month, we obtain stock-level climate beta for each stock-month for all US-based common stocks over June 2010 to May 2018 by running a time-series regression of stock excess returns on innovations in the CH climate change news index over the past 24 months while controlling for standard risk factors. When stocks are sorted into quintiles by their climate betas, the top quintile on average outperforms the bottom quintile by 0.36% per month (t-statistic = 2.97) on equal-weighted basis and by 0.29% per month (t-statistic = 2.22) on value-weighted basis. This excess return difference cannot be explained by standard risk exposures. By studying characteristics of climate beta stocks, we document that climate beta is positively associated with firm size, book-to-market ratio, institutional ownership, R&D expense over assets, and is negatively correlated with firm leverage. This is consistent with our expectation that ‘climate hedge’ firms are likely to be larger, higher-valued, more institution-owned, more innovative, and less levered. Interestingly, climate beta is positively related to the change in firm’s environmental score, but not to its level, and is negatively related to the Sautner et al. (2021) climate risk exposure captured in conversations in the firm’s conference calls. Importantly, using Fama and MacBeth (1973) regressions, we find that stock-level climate beta contains distinctive information from other proxies of a firm greenness in predicting future stock returns.

We next study possible drivers for the positive relation between stock-level climate beta and subsequent stock returns. These drivers can come from two ways: investors increasingly appreciate the holdings of climate-hedging stocks, driving up their prices (investor channel) and customers shift their demands for products of climate-friendly firms, boosting their profitability and valuations (customer channel). First, we show that stock climate betas are positively associated with future change in institutional ownership, indicating that institutional investors perhaps incorporate stocks with positive climate betas when forming their portfolios. Also, there is a positive relation between stock climate betas and the measure of stock-level price impact developed by Koijen and Yogo (2019). The finding is consistent with the idea that investors bid up prices of stocks that can effectively hedge against climate change. Second, stock-level climate betas positively forecast future firm gross profitability, return on equity, and return on asset. The evidence suggests that stock-level climate beta contains information about future firm financial fundamentals that might not be fully reflected in the current stock value. Overall, the interaction between these demand-driven and fundamentals-driven factors might push up the prices of high climate beta stocks over the recent period.

Finally, we examine whether high climate beta mutual funds earn higher returns by over-weighting high climate beta stocks. First, using mutual fund holdings, we find that high (low) climate beta mutual funds deliberately direct their fund flows into high (low) climate beta stocks. Second, we analyse if funds holding high climate beta stocks outperform. The quarterly stock holdings data are combined with the monthly stock-level climate betas to calculate investment value-weighted fund-level scores of climate beta stock holdings. Using portfolio sorting, we find that funds with the highest scores on average earn 0.19% higher (t-statistic = 2.67) than ones with the lowest scores in the next month, implying that mutual funds tilting their portfolios toward high climate beta stocks outperform. Third, by using time-series regressions, the return difference between funds holding high and those holding low climate beta stocks can significantly explain the return difference between high and low fund-level climate beta funds. Hence, we conclude that high climate beta funds, which effectively hedge against climate change risk, outperform by simply tilting toward high climate beta stocks that experience a significant appreciation over our sample period.

Our study makes several contributions to the existing literature. First, our findings are in line with the theoretical framework of Pastor et al. (2021) suggesting that there exists a possible wedge between expected and realized returns for sustainable assets. In equilibrium, the risk-adjusted expected returns on greener firms will be less due to investors' preferences for these firms' stocks. However, over a given period of time when climate concerns strengthen unexpectedly, green assets that hedge against climate risk outperform brown assets. This is consistent with the notion that sustainability concern is a relatively new phenomenon that comes to the fore over the past 15–20 years.[2] Pedersen et al. (2021) also consider the impact of a growing adoption of sustainable investing over time (i.e., a growing fraction of ESG-motivated investors or a greater ESG preference among them).[3] A future growth in sustainable investing would increase the price of sustainable stocks. If these flows are unexpected (or not fully reflected in the price for other reasons), then high-ESG stocks would experience a return boost during the period of this repricing of ESG.

Second, we contribute to the empirical debate on the association between ESG-related investing and performance in general. At the firm-level, the literature indicates mixed evidence of both under- and outperformance of stocks based on ESG characteristics. For example, Khan et al. (2016) find that firms with good ratings on sustainability issues classified as material outperform firms with poor ratings on these issues. In et al. (2019) show that a portfolio that is long carbon-efficient stocks and short carbon-inefficient stocks yields positive abnormal returns. On the other hand, Bolton and Kacperczyk (2021) suggest that investors demand higher returns on carbon-intensive firms as a compensation for exposure to carbon risk.[4] At the fund-level, reported results on performance of ESG-focused investors are also heterogeneous. Nofsinger and Varma (2014) show that responsible funds outperform otherwise similar funds during market crisis, but underperform in other periods. El Ghoul and Karoni (2017) find that the CSR score of the portfolio is negatively associated with risk-adjusted performance, while Brandon et al. (2021) suggest a positive link between risk-adjusted return and the sustainability footprint of an institutional investor. Indeed, while most earlier studies examine the differences in stock (or fund) returns as a function of ESG ratings that are inconsistent among data providers and infrequently updated (Chatterji et al., 2016;

[2]According to the *2020 Report on Sustainable and Impact Investing Trends*, the sustainable investing industry in the US has grown more than 25-fold since 1995, reaching $17.1 trillion – or 1 in 3 dollars – of the total US assets under professional management. This represents a compound annual growth rate of 14 percent over 1995–2020 and a 42 percent increase over the recent two years.

[3]According to the theoretical work of Pedersen et al. (2021), equilibrium asset prices are determined by an ESG-adjusted capital asset pricing model. The authors show that higher ESG assets have higher or lower equilibrium expected returns, depending on the wealth of three types of investors (i.e., ESG-unaware, ESG-aware, and ESG-motivated investors).

[4]For other empirical papers on ESG and equity returns, see Gompers et al. (2003), Edmans (2011), Flammer (2015), Krüger (2015), Dimson et al. (2015) for a positive relation, see Di Giuli and Kostovetsky (2014), Hong et al. (2019), Hsu et al. (2020), Hong and Kacperczyk (2009) for a negative relation.

Berg et al., 2020), our study relies on a more real-time measure of the aggregate climate change news. Also, other proxies for climate change exposure such as carbon emission are best at identifying “bad firms”, e.g., heavy emitters. This does not mean that light emitters are better at low-carbon technology and innovation. Our climate beta offers a clear distinction between assets that are expected to gain or lose, thus capturing other forward-looking aspects valued by investors in times of increased climate concern. Finally, our findings regarding the effect of climate beta are consistent at both firm- and fund-level.

The rest of the chapter proceeds as follows. Section 4.2 discusses the mutual fund data and the construction of climate change news indexes. Section 4.3 presents the findings about the effect of fund-level climate betas on mutual fund performance and investigates the robustness of our results. Section 4.4 explores the mechanism driving the performance of high climate beta mutual funds by examining their equity holdings. Section 4.5 concludes.

4.2. Data

4.2.1. Mutual fund data

Mutual fund returns, expenses, total net assets (TNA) and other fund characteristics are obtained from the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database for the sample period from July 2008 to June 2018.[5] We keep in our sample only funds that report returns on a monthly basis. Since this study focuses on diversified actively managed equity mutual funds, we follow prior studies to exclude international, balanced, sector, bond, money market, and index funds. To address incubation bias (Evans, 2010), we additionally remove the first eighteen months of returns on each fund. The common-stock holding information for funds holding equities is obtained from the Thompson Reuters Mutual Fund Holdings Database. We match the holdings database to the CRSP mutual fund database using MFLINKS files from WRDS.

[5]We restrict our main analysis to a sample period where the Crimson Hexagon (CH)’s negative sentiment climate change news index is available. We also perform robustness checks using different and longer sample periods where we base these analyses on other climate change concern indexes.

Funds usually have multiple share classes that typically differ in the fee structure and the target clientele. We aggregate such classes into a single observation. Specifically, we compute the TNA of each fund as the sum of its different share classes and calculate fund age as the age of its oldest share class. For all other fund characteristics (e.g., returns, fees), we compute the weighted average of the characteristics of the individual share classes, where the weights are the lagged share-class TNAs.

Our final sample comprises 2,781 unique actively managed equity mutual funds and 222,904 fund-month observations. Table 4.1 provides a summary description of the funds in our sample. An average fund earns a gross return of 0.87% and a net return of 0.79% per month over July 2008-June 2018. It is approximately 170 months old, manages on average $1.27 billion of assets, charges 1.11% in expenses, and generates turnover of 70%.

[Insert Table 4.1 about here]

4.2.2. Climate change news index

For our main analysis, we obtain the monthly Crimson Hexagon (CH)'s negative sentiment climate change news index that spans the period from June 2008 to May 2018.[6] CH climate change news index is a text-based marketwide index reflecting negative climate risk news (i.e., climate change concern) and being constructed by Engle et al. (2020). Based on the idea that climate change rises to the media's attention when there is a cause for concern, the index captures the intensity of discussions about climate change in over 1,000 news sources, including WSJ, NY Times, Reuters, BBC, CNN, and Yahoo News. Engle et al. (2020) conduct a variety of validation tests and show that the index reasonably reflects the aggregate negative view among investors about climate change risk at a given point in time. Following Engle et al. (2020), our analysis uses innovations in the CH climate change news index, which are the residuals from the first-order autoregressive

[6]Data for the Crimson Hexagon (CH)'s climate change news index is available on Stefano Giglio's website at https://sites.google.com/view/stefanogiglio

model. As reported in Panel A of Table 4.2, the CH climate change news innovations over our sample period have a mean of 0.000 and a standard deviation of 0.074, with the 25th and 75th percentiles at –0.036 and 0.027 respectively.

[Insert Table 4.2 about here]

For robustness, we consider two other climate change measures that might capture investors' attention to climate risk: monthly innovations in the Wall Street Journal (WSJ) climate change news index (Engle et al., 2020) and monthly log difference in Internet search volume intensity (SVI) on topic "climate change" constructed by Google Trends. Different from the CH climate change news index, the WSJ climate change news index is drawn from a single source and without determining if the news sentiment is negative or positive. The WSJ index covers a longer period from February 1984 to June 2017. For the SVI index, Google Trends aggregates online search queries in different languages and keywords if they are related to climate change issues. We restrict the search location to the U.S. and the time series for the monthly SVI changes is from February 2004 to December 2019.

Panel B of Table 4.2 reports the correlations between innovations in climate change indexes and standard risk factors in the asset pricing literature based on their overlapping time series. Fama and French (1993) three factors (*MKT*, *SMB*, and *HML*) and the momentum factor (*UMD*) are collected from Kenneth French's website.[7] As shown in Panel B of Table 4.2, the CH climate change news innovations have a correlation of 0.49 with the WSJ climate change news innovations and a correlation of 0.42 with the SVI changes. The CH climate change news innovations are only modestly correlated with other standard risk factors.

[7]The data is available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

4.3. Baseline results

4.3.1. Portfolio sorts

We first perform portfolio sorts to examine the relation between fund-level climate beta and fund returns. At the end of each month starting from June 2010 to May 2018, we sort mutual funds into quintiles based on the fund climate beta (i.e. loading on the CH climate change news innovations) estimated from a rolling window of the most recent 24 months (including the current month), with the first rolling window covering the period from July 2008 to June 2010. We exclude mutual funds with TNA of less than \$15 million at the end of the current month. The fifth (first) quintile consists of funds with the highest (lowest) climate betas. We then track the portfolio returns over the next month, which starts from July 2010. We rebalance these portfolios every month and obtain the time series of returns for each quintile portfolio from July 2010 to June 2018.

In particular, for each mutual fund i in each month t, we estimate the climate beta ($\beta_{Fund}^{Climate}$) from the monthly regression of mutual fund excess returns on innovations in the monthly CH climate change news index over a 24-month rolling window (covering month $t-23$ up to month t) with a requirement of at least 18 months of non-missing fund returns.[8] The regression is as follows:

$$r_{Fund_{i,t}} = \alpha_{i,t} + \beta_{Fund_{i,t}}^{Climate} \times CH\_Climate_t + \boldsymbol{\beta}_{\boldsymbol{i,t}}' \times \boldsymbol{F_t} + \varepsilon_{i,t} \tag{4.1}$$

where $r_{Fund_{i,t}}$ is the excess return (in excess of the risk-free rate) of fund i in month t, $CH\_Climate$ is innovations in the monthly CH climate change news index, and the vector $\boldsymbol{F}$ contains the Fama and French (1993) three factors and the Carhart (1997) momentum factor.[9] $\beta_{Fund}^{Climate}$ is fund-level climate beta capturing the fund's covariance with innovations in the climate change news index. The use of a rolling window allows for time-variation in the beta estimates.

[8]For ease of presentation, we rescale by multiplying the CH climate change news innovations by 10.

[9]We obtain qualitatively similar results when using alternative combinations of risk factors as control variables in Equation (4.1). Results are provided in Appendix C.

By construction, a greater $\beta_{Fund}^{Climate}$ indicates an increase in the fund's return when innovation in the climate change news index increases.

We track the gross returns for the quintile portfolios over the next month after portfolio formation. These portfolios are rebalanced every month. Table 4.3 presents the results for the performance of these quintiles sorted by mutual fund climate beta. Specifically, we report the time-series average of mutual fund excess gross returns across five quintiles. Each quintile has about 317 funds on average and is well diversified. Over our sample period from July 2010 to June 2018, there is a monotonic increase in the average monthly equal-weighted mutual fund portfolio returns, from 1.08% in the lowest climate beta quintile to 1.29% in the highest climate beta quintile. The average return difference between the two extreme quintile portfolios (i.e., portfolios 5 and 1) is 0.21% per month, or 2.53% per year, with a t-statistic of 3.14.

[Insert Table 4.3 about here]

We estimate portfolio-level alphas (risk-adjusted returns) by performing time-series regressions of the monthly excess returns of each quintile portfolio on Fama and French (1993) three factors, the momentum factor (Carhart, 1997), and the liquidity factor (Pástor and Stambaugh, 2003). As shown in Table 4.3, on a risk-adjusted basis, the quintile portfolio with the lowest climate betas delivers an alpha ($FFCPS\ \alpha$) of –0.20% (t-statistic = –3.47), indicating a negative abnormal performance. Meanwhile, the quintile portfolio with the highest climate betas generates an alpha of 0.03% (t-statistic = 0.52) per month. The spread in alphas between the two extreme quintile portfolios is 0.24% per month and is statistically significant (t-statistic = 3.72).

We also show in Table 4.3 that the climate beta effect is both statistically and economically significant when portfolio returns are weighted by fund TNA. In particular, the underperformance of funds in the lowest climate beta, compared to the highest climate beta, quintile is economically large, generating an average return spread of 0.19% per month (t-statistic = 1.81). The associated alpha ($FFCPS\ \alpha$) difference between these two quintiles is 0.26% per month and is statistically significant (t-statistic = 2.89). Overall, the results from portfolio sorts indicate that climate beta is significantly and positively associated with both next month mutual fund excess returns and alphas after adjusting for systematic risk factors.

Figure 4.1 plots the spreads in equal-weighted one-month-ahead excess return between the high and low climate beta quintile portfolios. The series begin in July 2010 as we use a 24-month formation period. Panel A shows that the return spreads are positive for nearly two thirds of the months in our sample period. Panel B plots the cumulative return difference between the high and low climate beta quintile portfolios. We observe a more pronounced effect of climate beta on mutual fund returns in the second half of our sample period (i.e., in the more recent period).

[Insert Figure 4.1 about here]

We conduct a series of sensitivity tests. First, to mitigate the concern about the precision of climate beta estimates, we use alternative combination of risk factors, such as additionally including liquidity factor (Pástor and Stambaugh, 2003) or investment and profitability factors (Fama and French, 2015), as control variables in Equation (4.1). Second, instead of tracking returns from the month immediately following portfolio formation, we skip one month. Third, we use a rolling window of 36 months instead of 24 months to estimate a fund's climate beta. In all specifications, our inference remains robust. To conserve space, we report these additional results in Table C2.1 of Appendix C.

We also investigate the long-term effect of fund-level climate beta by calculating monthly equal-weighted returns and alphas of the climate beta quintiles from two to six months after portfolio formation. The results are reported in Table C2.2 of Appendix C. During the second month after portfolio formation, the difference in excess returns between the high and low fund-level climate beta quintiles is 0.22% per month (t-statistic = 3.28). Similarly, the difference is 0.21% (t-statistic = 3.42) during the third month after the portfolio formation. The predictive power of climate beta on future mutual fund returns diminishes as one moves further away from the portfolio formation month and becomes insignificant after fifth month. Therefore, the climate beta effect persists several months into the future.

4.3.2. Fama-MacBeth regressions

The findings from portfolio-level analysis indicate that a portfolio of mutual funds with high climate betas yields significantly higher future return than the ones with low climate betas. In this section, we perform Fama and MacBeth (1973) regressions that utilize the entire cross-sectional information in the data to investigate whether the relation between fund climate betas and expected fund returns persists after simultaneously controlling for several known determinants of fund performance and fund styles. Specifically, at the end of each month from June 2010 to May 2018, we run the following cross-sectional regressions:

$$r_{Fund_{i,t+1}} = \psi_{0,t} + \psi_t \times \beta^{Climate}_{Fund_{i,t}} + \phi_t' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t+1} \tag{4.2}$$

where $r_{Fund_{i,t+1}}$ is excess return of fund i in month $t+1$, $\beta^{Climate}_{Fund_{i,t}}$ is climate beta of fund i that is estimated from Equation (4.1), using fund returns in a rolling window of 24 months from month $t-23$ up to month t. Thus, the key independent variable is fund-level climate beta, computed from a backward-looking window prior to the return evaluation period. $\boldsymbol{Z}_{i,t}$ is a vector of predetermined fund characteristics, including fund size, fund age, past fund flow, turnover ratio, expense ratio, manager tenure, tracking error, R-squared, past alpha, and fund style dummies. The details of these variables are provided in the Appendix. All independent variables are winsorized at 0.5% level.

Table 4.4 presents the time-series average of the slope coefficients, the corresponding Newey-West adjusted t-statistics (with 3 lags), and the average adjusted R^2 from the monthly regressions (Equation (4.2)) over June 2010 to May 2018.

[Insert Table 4.4 about here]

The univariate regression result in Specification (1) indicates that climate beta positively predicts mutual fund returns in the cross section. The average slope coefficient, ψ_t, from regressing fund excess returns on their climate betas is 0.188 (t-statistic = 3.13). The economic magnitude of the climate beta effect is comparable to that shown in the univariate portfolio sorts. In particular, when climate beta increases from –0.57 (its average level in the bottom quintile in Table 4.3) to 0.79 (its average level in the top quintile), monthly mutual fund excess return increases by 0.26% on average (i.e., 0.188×1.36).

We obtain similar evidence from the multivariate regressions. In Specification (2), after controlling for fund characteristics and several skill measures, we still observe a positive and significant association between fund-level climate beta and next month's mutual fund returns. We further include fund style dummies in Specification (3), our inference remains robust with an average coefficient on climate beta of 0.125 (t-statistic = 2.53).

Instead of using fund excess return as the dependent variable in the regression Equation (4.2), we now use fund alpha. The alpha for fund i in month $t+1$ is calculated as the difference between the fund excess return in month $t+1$ and the products of its factor loadings estimated at the end of month t and factor realizations in month $t+1$, that is,

$$\alpha_{i,t+1} = r_{Fund_{i,t+1}} - \boldsymbol{\beta}'_{i,t} \times \boldsymbol{F}_{t+1} \tag{4.3}$$

where the factor loadings $\boldsymbol{\beta}_{i,t}$ are estimated from the regression of fund i's excess returns on common risk factors over the past 24-month data, and the vector $\boldsymbol{F}_{t+1}$ denotes realized returns of these factors in month $t+1$.

In Specification (4) of Table 4.4, we compute fund alpha ($FFC\ \alpha$) using the Fama and French (1993) three factors and the Carhart (1997) momentum factor as risk factors in Equation (4.3). After controlling for fund characteristics and style dummies, we find that fund-level climate beta is positively related to fund alpha. As shown in Specification (4), the regression coefficient on fund-level climate beta is 0.070 and is statistically significant at 10% level (t-statistic = 1.78). We next augment the factor model by adding the Pástor and Stambaugh (2003) liquidity factor to estimate the fund alpha ($FFCPS\ \alpha$). Using $FFCPS\ \alpha$ as the dependent variable, the coefficient on fund climate beta is 0.097 (t-statistic = 2.00).

Overall, our findings from both portfolio sorts and cross-sectional regressions show a positive and significant association between fund-level climate beta and subsequent mutual fund performance, even after controlling for fund characteristics and adjusting for standard risk factors.

4.3.3. Additional robustness checks

4.3.3.1. Alternative climate change measures

Our main analysis adopts the CH climate change news index. In this subsection, we investigate whether our inference is robust to other measures capturing climate change concern. As an alternative measure, we first consider innovations in the WSJ climate change news index that span a longer period from February 1984 to June 2017 and are also developed by Engle et al. (2020). However, there are several potential shortcomings with the WSJ news index as it is based on a single source and can inaccurately consider discussions of positive climate news as increases in climate risk.

Table 4.5 reports the results of portfolio sorts based on fund-level climate betas with respect to innovations in the WSJ climate change news index. Our time series of portfolio returns starts from February 1986 as the first 24-month window is used to compute the first climate beta. Over February 1986 to July 2017, we observe a weak positive relation between fund-level climate beta and next month mutual fund performance. In particular, the differences in equal-weighted excess return and $FFCPS$ alpha between the high and low climate beta quintiles are 0.14% per month (t-statistic = 2.15) and 0.11% per month (t-statistic = 1.64) respectively. For value-weighted portfolio returns, we also observe a positive but insignificant return and alpha spreads between these two extreme quintiles.

Engle et al. (2020) show that the intensity of climate news coverage has increased steadily since about the year 2000. This is consistent with the notion that attention about climate change has become more salient among investors recently. Thus, we break this sample period into pre- and post-2000. As shown in Table 4.5, there is no significant pattern in average returns and alphas for portfolios (both equal-weight and value-weight) sorted by climate betas in period before 2000. For period from January 2000 to July 2017, result for equal-weighted portfolios shows that the high climate beta mutual funds, on average, outperform the low climate beta mutual funds by 0.25% per month (t-statistic = 2.82) and by 0.22% per month (t-statistic = 2.54) on a risk-adjusted basis. Thus, the spreads in excess returns and alphas are quite close to those that are based on the CH climate change news index. The inference is still insensitive to test based on value-weighted portfolios.

[Insert Table 4.5 about here]

As another alternative measure reflecting climate change concern, we consider log differences in monthly SVIs on search topic "climate change" constructed by Google Trends. We draw qualitatively similar conclusion using SVI index. For example, based on equal-weighted quintile portfolios, the average return difference between the high and low climate beta quintiles is 0.21% per month (t-statistic = 3.16) and the difference in alpha ($FFCPS\ \alpha$) is 0.16% per month (t-statistic = 2.35) over the period from February 2006 to December 2019. Based on value-weighted portfolio sorts, the return spread between the two extreme quintiles is 0.18% per month (t-statistic = 2.28) and the spread in alpha is 0.11% per month, but not statistically significant (t-statistic = 1.49). For brevity, these results are reported in Table C2.3 of Appendix C.

In sum, our evidence on the positive relation between fund-level climate beta and future fund performance is insensitive to the choice of alternative measures capturing climate change concern. We prefer to the use of the CH negative sentiment climate change news index as our main measure because it is constructed from a large collection of news article and is designed to specifically focus on negative climate change news.

4.3.3.2. Results from net-of-fee returns

So far, our analysis has focused on fund gross performance before fees, which provides a picture of the value created by fund managers. However, if investment management fees charged by fund managers are systematically correlated with their climate betas, the investment into high climate beta funds is of no monetary value attributed to their investors. To address this question, we repeat the tests of portfolio sorts using net-of-fee returns, which are fund investors' payoffs.

[Insert Table 4.6 about here]

As shown in Table 4.6, there is a significant and positive association between mutual funds' net returns and their climate betas. Based on equal-weighted portfolios, mutual funds in the high climate beta quintile yield an average excess net return of 1.21% (t-statistic = 3.49) and a $FFCPS$ alpha of –0.05% (t-statistic = –0.83) per month, while funds in the low climate beta quintile earn an average excess net return of 1.00% (t-statistic = 2.98) and an alpha of –0.28% (t-statistic = –4.80) per month. The difference in monthly excess net-of-fee return between these two quintiles is 0.21% (t-statistic = 3.06) while the difference in alpha is 0.23% (t-statistic = 3.63). Based on value-weighted portfolios, we observe a spread of 0.19% per month (t-statistic = 1.80) in excess net return and a spread of 0.26% per month (t-statistic = 2.87) in alpha between the high and low fund-level climate beta quintiles. Therefore, our analysis using net-of-fee fund returns leads to the same inference regarding the association between climate beta and mutual fund performance. In other words, investors benefit from investing in high climate beta funds during our sample period from July 2010 to June 2018.

4.4. What explains the climate beta - fund performance relation?

Previous section shows that high climate beta mutual funds outperform otherwise similar mutual funds. In this section, we explore whether the rise in responsible investment and consumption that aims to mitigate climate change has impacted the performance of mutual funds' portfolio firms. Possibly, positive climate beta stocks, i.e., climate hedge, have recently earned higher excess returns, which in turn have benefited mutual funds tilting toward these stocks and led to a positive relation between fund-level climate beta and fund performance. To test this hypothesis, we examine three questions: (1) Is there a positive cross-sectional relation between stock-level climate beta and subsequent stock return?, (2) If there is a relation, which factors drive this effect?, (3) Do high climate beta mutual funds outperform by simply holding high climate beta stocks?

4.4.1. Stock-level climate beta and future stock returns

Monthly equity data for returns and several stock characteristics are obtained from the Center for Research and Security Prices (CRSP) and Compustat for the period from July 2008 to June 2018. Each month, we include all US-based common stocks trading on the NYSE, AMEX, and NASDAQ with an end-of-month stock price of at least $1 in our sample to ensure that small and illiquid stocks do not drive our results. The final sample contains on average 3,107 equity observations per month.

To obtain stock-level climate beta for each stock, we now perform a similar regression as in Equation (4.1), but using stock excess returns, instead of mutual fund excess returns, in the left-hand side. Using a rolling window of 24 months with at least 18 months of return observations, we acquire the time series of climate betas for each stock j at the end of June 2010 to May 2018. Next, we perform portfolio sorts, where quintiles are formed every month by sorting stocks based on their stock-level climate betas and one-month-ahead returns (from July 2010 to June 2018) are computed to examine whether there is a significant return difference between the high and low climate beta stock quintiles. Panel A of Table 4.7 reports the time-series average of one-month-ahead excess stock returns for each of climate beta-sorted quintiles. We present results for both equal-weighted and value-weighted portfolio returns.

[Insert Table 4.7 about here]

We find a monotonic increase in the average monthly equal-weighted stock portfolio returns during our sample period. Specifically, stocks in the lowest climate beta quintile have a monthly equal-weighted average excess return of 1.13%. The sharpest increase in excess return occurs in quintile 2, earning an average of 1.36% per month. Stocks in the highest climate beta quintile earn an equal-weighted average of 1.49% per month. The average return spread between the extreme climate beta equity quintiles is 0.36% with a significantly positive t-statistic of 2.97, indicating that stocks with higher climate betas have significantly higher next-month excess returns.[10]

We then examine whether this excess return spread can be explained by standard risk factors. Incorporating standard market, size, value, and momentum factors, we find the spread of 0.28% (t-statistic = 2.29) in the risk-adjusted returns between the two extreme climate beta stock quintiles. Using five-factor model of Fama and French (2015) augmented with the momentum factor, the spread in alphas between these two extreme quintiles is 0.29% per month and is still statistically significant (t-statistic = 2.32).

Panel A of Table 4.7 also reports results for the value-weighted portfolios and the findings are quite similar to those from equal-weighted portfolios. In particular, the excess return difference between the two extreme climate beta stock quintiles is equal to 0.29% per month on average and is statistically significant (t-statistic = 2.22). The corresponding 6-factor alpha difference is 0.26% per month (t-statistic = 1.85). Overall, there is a positive relation between climate betas of stocks and their future excess returns in the cross section.

We next investigate the characteristics of stock-level climate beta via a series of cross-sectional regressions of stock j's climate beta in month t on various contemporaneous characteristics of stock j.[11] We reports the time-series averages of the slope coefficients and the corresponding t-statistics in Panel B of Table 4.7. Several findings are in line with prior expectations about a firm's climate risk exposure. First, positive coefficient on firm size in Specification (1) indicates that high climate beta firms tend to be larger, consistent with the notion that larger firms are more likely to diversify across different operation activities and have greater lobbying powers to better hedge against climate risks. Second, low climate beta funds are associated with higher book-to-market ratio, implying that high climate risk exposures lead to low firm valuations as expected in prior

[10]We obtain qualitatively similar findings using sample that excludes stocks with less than $5 at the end of each month. Results are available upon request.

[11]Definitions of firms' characteristics are detailed in Appendix C1.

studies (Bolton and Kacperczyk, 2021; Sautner et al., 2021). Third, aligned with Dyck et al. (2019) finding that institutional investors increase firms' environmental performance, we document a positive relation between stock-level climate beta and institutional ownership. Fourth, high (low) climate beta firms are associated with low (high) leverage, measured as debt-to-asset ratio, and are hence in better (worse) position to cope with climate risks. Fifth, climate beta is positively related to R&D expenses over assets, suggesting that high climate beta firms are more likely to involve in clean research and investment.

Further, we examine the relation between climate beta and alternative measures of firm-level climate risk exposure. We consider the KLD environmental score (E-Score), the change in E-Score, and the Sautner et al. (2021)'s text-based measure of climate change exposure, risk, and sentiment extracted from firms' conversations in quarterly conference calls.[12] Specifications (2) and (3) in Panel B of Table 4.7 show that stock-level climate beta has no significant relation with the current level of E-Score but has a positive relation with the change in this score. The finding suggests that high climate beta firms are associated with an improvement in environmental performance. Also, consistent with our expectation, Specification (4) documents a significant negative relation between climate beta and the text-based measure of climate change exposure. Furthermore, the negative coefficient on climate change risk in Specification (5) implies that analysts more frequently discuss about climate change risks during conference calls of firms with low climate beta. Overall, we find some meaningful relations between our market-based climate beta and other measures of climate risk exposure. However, the R-squared of these regressions are only about 8 percent, suggesting that existing proxies of climate risk exposure only explain a small fraction of the variation in stock-level climate betas.

In Table C2.4 of Appendix C, we perform Fama and MacBeth (1973) regressions of next month stock excess returns on stock-level climate betas, controlling for several stock characteristics and some alternative measures of climate change exposure over June 2010 to May 2018. Across

[12]Data for the Sautner et al. (2021)'s climate change exposure is available to download at: https://osf.io/fd6jq/.

different specifications, we consistently observe a positive relation between stock-level climate beta and subsequent stock returns. The average coefficient on stock climate beta is 0.35 and is statistically significant (with t-statistics ranging from 2.35 to 2.53). Therefore, stock climate beta contains distinctive information from other proxies of climate risk exposure in predicting future stock returns.

4.4.2. Drivers of stock climate beta - stock return relation

The previous section shows that stocks with higher climate betas yield higher subsequent returns. In this section, we investigate possible drivers of this relation.

4.4.2.1. Does stock climate beta predict investor demand?

A possible explanation for the positive relation between stock-level climate beta and subsequent stock returns is that stock-level climate beta correlates with future investor demand. We consider the change in institutional ownership and the stock-level price pressure defined as the product of the stock-level elasticity of demand (Koijen and Yogo, 2019) and the change in institutional ownership.[13] We perform Fama and MacBeth (1973) regressions to examine the relation. Control variables include market beta, size, book-to-market, momentum, and reversal. Results are reported in Table 4.8.

[Insert Table 4.8 about here]

First, Specification (1) of Table 4.8 uses the change in institutional ownership (in percent, obtained from 13F reports, and led by three months) as the dependent variable. Result indicates that stock climate beta correlates positively with change in institutional holdings. Specifically, the coefficient on stock climate beta is 0.166 and is statistically significant with a t-statistic of 2.37. The

[13] Koijen and Yogo (2019) suggest a demand system approach to asset pricing. They argue that to some extent, asset prices are determined by institutional investors' demand. They use 13F stock holdings to derive explicit measures of price impact for each stock, which quantify the extent to which a demand shock from an investor impacts the price of a given stock. These measures are defined as elasticities. The data is available on Koijen's website at https://koijen.net/code-and-data.html

economic effect is noticeable. The increase in stock climate beta from the lowest to the highest climate beta quintiles is associated with an increase of 0.18% in institutional ownership in the next quarter. This suggests that institutional investors are increasingly incorporating stocks with high climate betas when forming their portfolios.

Second, investors' preference for high climate beta stocks might bid up their prices, leading to a stronger price pressure in the sense of Koijen and Yogo (2019) for stocks with higher climate betas. In Specification (2) of Table 4.8, we regress the quarterly price pressure measure at the stock-level (led by three months) on stock climate betas. We find that stock climate beta is significantly and positively associated with stock-level price pressure. In particular, the coefficient on stock climate beta is 0.316 (t-statistic = 2.09). This evidence supports the idea that investors bid up prices of stocks with high climate betas.

4.4.2.2. Does stock climate beta predict future firm fundamentals?

Another possibility for the positive relation between stock climate beta and future stock returns is that stock climate beta correlates with future firm fundamentals. Specification (3) of Table 4.8 uses future gross profitability, defined as firm's gross profit over total assets as in Novy-Marx (2013) over the next 12 months, as dependent variable in the cross-sectional regression. The current level of gross profitability is included as an additional control variable. We find that stock-level climate beta is a strong predictor of future firm gross profitability. The coefficient on stock climate beta is 0.005 with a t-statistic of 2.61. In Specification (4) of Table 4.8, stock-level climate beta positively correlates with future return on equity, even after controlling for the current level of ROE. We also find supportive evidence using future return on asset as dependent variable in Specification (5) (the coefficient on stock climate beta is 0.004 with a t-statistic of 3.66). Therefore, stock-level climate beta might contain information about future firm fundamentals that might not be fully priced into the market.

So far, the findings suggest that stock-level climate beta positively and significantly correlates with future firm fundamentals. At the same time, investors tilt their portfolios toward stocks with higher climate betas, leading to higher price pressure for these stocks. The interplay between these two effects might push up the prices of high climate beta stocks over our sample period.[14]

4.4.3. Do high climate beta funds outperform by holding high climate beta stocks?

We have showed that over our sample period, high climate beta stocks earn higher expected returns. In this section, we investigate whether high climate beta mutual funds deliberately tilt their holdings toward high climate beta stocks, whether mutual funds overweighting high climate beta stocks outperform, whether high climate beta funds outperform as indicated in Section 3 by simply holding high climate beta stocks.

First, to understand whether high climate beta mutual funds take deliberate actions into their investments, we examine how flows into (out of) high and low climate beta funds are invested into high and low climate beta stocks. Particularly, in each quarter and for each mutual fund, we analyze the mutual fund holdings and define the flows-based climate beta stock trading ($Flows\_Climate$) as follows:

$$Flows\_Climate_{i,t} = \frac{\sum_j \left[D_{j,i,t} - D_{j,i,t-1} \times \left(1 + r_{j,t}\right)\right] \times \beta^{Climate}_{Stock_{j,t}}}{\sum_j D_{j,i,t-1}} \tag{4.4}$$

where $D_{j,i,t}$ is the investment value of stock j in fund i in quarter t, $r_{j,t}$ is the return of stock j in quarter t, and $\beta^{Climate}_{Stock_{j,t}}$ is climate beta of stock j in month t. A positive $Flows\_Climate_{i,t}$ implies that fund i, on average, invests into (out of) positive (negative) climate beta stocks when receiving inflows (outflows) in quarter t, and vice versa.

We examine the relation between fund-level climate beta and $Flows\_Climate$. Each quarter, we sort mutual funds into quintiles based on their fund-level climate betas and within these

[14]Table C2.5 of Appendix C examines the long-term effect of stock-level climate beta on expected stock returns. The excess return difference between high and low climate beta stocks remains significant until the fifth month after the portfolio formation month. This is consistent with the idea that stock-level climate betas positively correlate with future firm fundamentals and institutional demand.

quintiles, we compute the mean values of $Flows\_Climate$. Table 4.9 reports the time-series average of the quarterly mean values of $Flows\_Climate$ for each quintile.

[Insert Table 4.9 about here]

We find that high (low) climate beta mutual funds are associated with positive (negative) $Flows\_Climate$. The difference in $Flows\_Climate$ between high and low climate beta funds is 0.81 (t-statistic = 3.25). This finding indicates that high (low) climate beta mutual funds deliberately direct their flows into high (low) climate beta stocks.

Second, to analyze if mutual funds tilting their portfolios toward high climate beta stocks outperform, we require mutual fund holdings that are obtained from the Thomson Financial Mutual Fund Holdings database. We combine the quarterly stock holdings data with the monthly stock-level climate betas to calculate the monthly fund-level score of climate beta stock holdings. Specifically, using stocks in fund i's most recently reported portfolio holdings, we define the fund-level score of climate beta stock holdings ($Climate\_Score$) as follows:

$$Climate\_Score_{i,t} = \sum_{j} w_{j,i,t} \times \beta_{Stock_{j,t}}^{Climate} \tag{4.5}$$

where $w_{j,i,t}$ is the investment weight of stock j in fund i in month t based on the most recent report and $\beta_{Stock_{j,t}}^{Climate}$ is climate beta of stock j in month t. The higher (lower) $Climate\_Score$ implies that the fund invests more into stocks with high (low) climate betas.

Now, we perform portfolio sorts, where quintiles are formed every month by sorting mutual funds based on their level of $Climate\_Score$ and one-month-ahead returns (from July 2010 to June 2018) are calculated to examine if mutual funds overweighting high climate beta stocks outperform in the next month.

[Insert Table 4.10 about here]

Table 4.10 presents results for both mutual fund excess returns and alphas across $Climate\_Score$-sorted portfolios. We observe significant return and alpha difference between funds holding high climate beta stocks and ones holding low climate beta stocks. In particular, for equal-weighted portfolios, funds holding low climate beta stocks (i.e., quintile 1) show an average excess return of 1.12% per month (t-statistic = 3.28) and a $FFCPS$ alpha of –0.14% per month (t-statistic = –3.23), indicating a significantly negative risk-adjusted return. Meanwhile, funds holding high climate beta stocks (i.e., quintile 5) deliver an average excess return of 1.31% per month (t-statistic = 3.74) and a $FFCPS$ alpha of 0.04% per month (t-statistic = 0.81). The return difference between the two extreme quintiles is 0.19% per month (t-statistic = 2.67) and the associated alpha difference is 0.19% per month (t-statistic = 3.14). We also find similar conclusion regarding the outperformance of funds holding high climate beta stocks using value-weighted portfolios.

The next question is whether high climate beta funds outperform by simply overweighting high climate beta stocks. So, we examine if the excess return difference between funds holding high and low climate beta stocks (in Table 4.10) can explain the excess return difference between the high and low climate beta funds (in Table 4.3). To do this, we perform a time-series regression of the monthly return spreads between high and low climate beta mutual funds on monthly return spreads between funds holding high and low climate beta stocks, controlling for standard risk factors. Specifically, the regression is defined as:

$$r_{\beta_{Fund}^{Climate},t+1} = \alpha_P + \theta \times r_{Climate\_Score,t+1} + \boldsymbol{\beta_P'} \times \boldsymbol{F}_{t+1} + \varepsilon_{P,t+1} \tag{4.6}$$

where $r_{\beta_{Fund}^{Climate},t+1}$ is month $t+1$ return spread between the fifth and first quintile of mutual funds sorted by fund-level climate beta at the end of month t, $r_{Climate\_Score,t+1}$ is the month $t+1$ return spread between the fifth and the first quintile of mutual funds sorted by $Climate\_Score$ at the end of month t, $\boldsymbol{F}_{t+1}$ is a vector of standard risk factors in month $t+1$. Table 4.11 reports the results.

[Insert Table 4.11 about here]

Regarding equal-weighted portfolios, as indicated in Specification (3) of Table 4.11, controlling for $r_{Climate\_Score}$ alone reduces the return spread (constant coefficient) between high and low climate beta funds from 0.21% per month (t-statistic = 3.14) to 0.08% per month (t-statistic = 1.88).

The coefficient on $r_{Climate\_Score}$ is 0.68 and statistically significant with the t-statistic of 8.29. Also, an adjusted R^2 of 0.49 implies that the outperformance of high climate beta mutual funds can be largely due to these funds holding high climate beta stocks. In Specification (4), additional control for standard risk factors (including market, size, value, and momentum) makes this return spread insignificant (constant coefficient = 0.07 with a t-statistic = 1.42). We reach a similar conclusion by checking value-weighted portfolios. In particular, as seen in Specification (7), $r_{Climate\_Score}$ can fully explain the return spread between the high and low climate beta funds (constant coefficient = 0.01, t-statistic = 0.17, and adjusted R^2 = 0.44).

To summarize, high climate beta funds outperform low climate beta funds by simply tilting their holdings toward higher climate beta stocks, which experience a significantly stronger increase in value over our sample period.

4.5. Conclusion

Survey on institutional investors indicates that climate risks have important financial implications for their portfolio firms and many investors integrate climate risks into their investment processes (Krueger et al., 2020). In this study, we propose a new measure to identify mutual funds that are positively or negatively affected by climate change concern. Specifically, we use fund-level climate beta, i.e., the sensitivity of each mutual fund returns to innovations in climate change news index, to capture the fund's ability to hedge against climate change and examine its predictive power for the cross-section of mutual fund returns.

In a portfolio sorting analysis, high climate beta funds, i.e., better hedging against climate change, outperform low climate beta funds by 0.21% per month on average over the period from July 2010 to June 2018. The risk-adjusted return difference between the two extreme quintiles after controlling for common risk factors is still economically large and statistically significant. Using Fama and MacBeth (1973) regressions, we find that the positive relation between fund-level climate beta and fund returns remains significant after controlling for observable fund characteristics and fund styles. This return predictability evidence is robust to alternative measures of climate change concern.

One explanation for the outperformance of mutual funds that more effectively hedge against climate change is that such funds tilt their portfolios towards high climate beta stocks, which experience significant increases in value over our sample period. Using stock-level climate betas, we find that high climate beta stocks earn a monthly return of 0.36% higher than low climate beta stocks. Such return spread is arguably driven by better firm fundamentals as well as increasing investor demand for stocks that hedge against climate risk. We then show that the holding of high versus low climate beta stocks can fully explain the return difference between high and low climate beta funds.

We contribute to the literature by showing that the incorporation of climate change concern into investment processes can be motivated by financial performance. During period when the consumers' demand for climate-friendly products and the interest of investors for stocks with high climate-hedging potential keeps growing, price of such 'climate hedge' stocks might experience a stronger boost, benefiting funds that tilt their investments towards these stocks. However, when the period of increasing adoption of sustainable investing or consuming is over and high climate beta stocks are perhaps traded at a premium, investment strategies that hedge against climate change should earn lower, not higher, expected returns for their hedging reason.

Figure 4.1: Difference in return between high and low climate beta mutual fund quintiles
At the end of each month from Jun 2010 to May 2018, we sort funds into quintiles according to their climate betas and track their returns over the next one month. Fund-level climate beta is estimated from a regression of mutual fund excess returns on innovations in the CH negative sentiment climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. Panel A plots the time series of the difference in monthly equal-weighted gross returns between the high and low climate beta fund quintiles. Panel B plots the cumulative difference in gross returns between these two extreme quintiles.

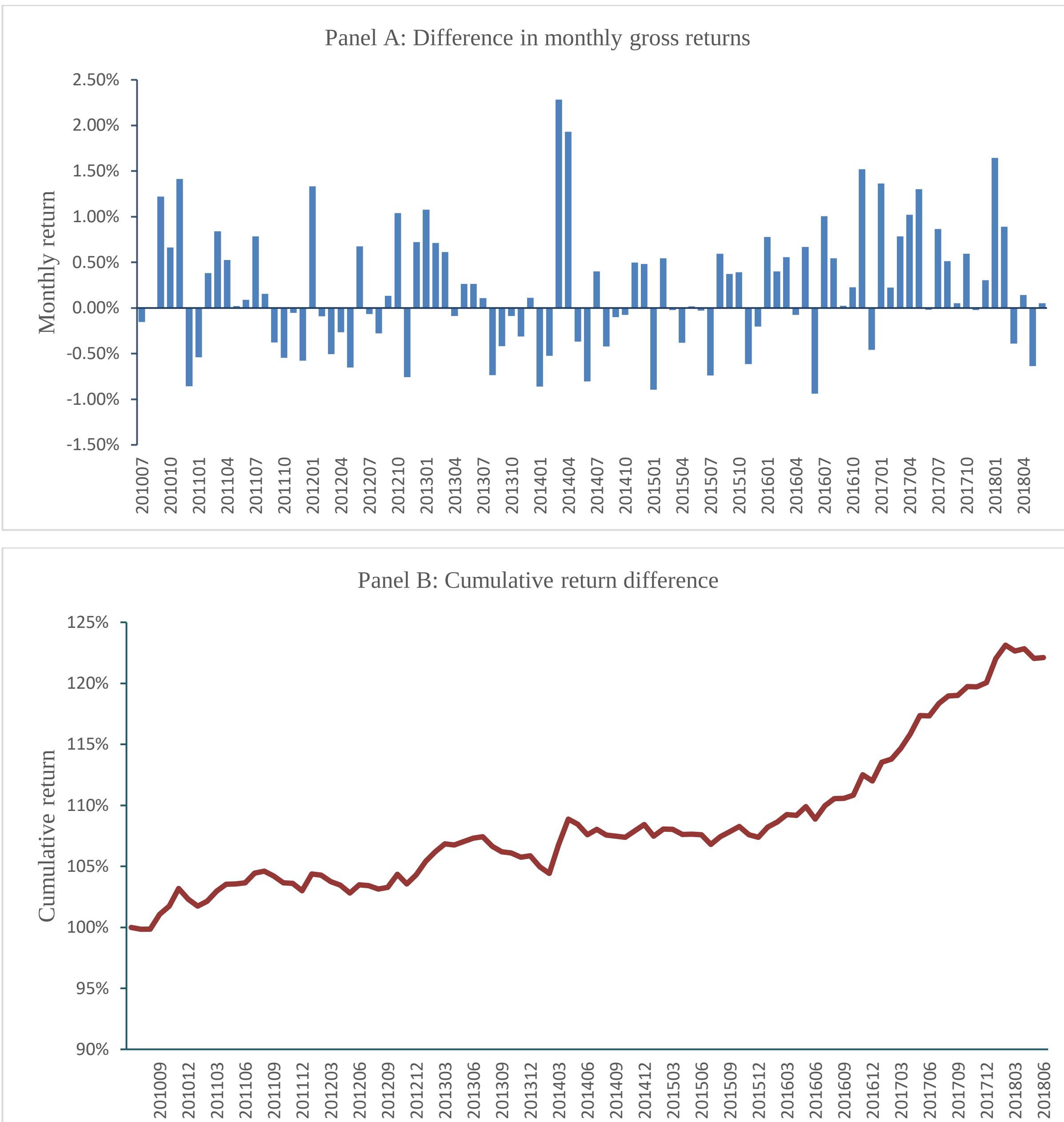

Table 4.1: Summary statistics of active equity mutual funds

The table summarizes the returns and characteristics of all actively managed equity mutual funds. All values are computed as the time series average of the monthly cross-sectional means, distribution statistics, and percentiles. The sample contains 2,781 unique funds and 222,904 fund-month observations. All of these variables, except fund returns, are winsorized each month at the 0.5% level. The sample period spans from Jul 2008 to Jun 2018.

	Mean	STD	P10	P25	P50	P75	P90
Gross return (%)	0.87	1.74	–1.13	–0.15	0.86	1.89	2.89
Net return (%)	0.79	1.73	–1.20	–0.23	0.79	1.81	2.80
Fund Size (TNA)	1271	4996	14	58	242	930	2657
Fund Flow	0.00	0.06	–0.03	–0.01	0.00	0.01	0.03
Fund Age (month)	170	119	38	90	158	221	295
Expense	0.011	0.004	0.007	0.009	0.011	0.013	0.015
Turnover	0.70	0.89	0.15	0.28	0.52	0.86	1.32

Table 4.2: Summary statistics of climate change indexes

Panel A describes the measures of climate change concern fluctuations, including innovations in the monthly Crimson Hexagon (CH) negative sentiment climate change news index (from Jul 2008 to May 2018), innovations in the monthly Wall Street Journal (WSJ) climate change news index (from Feb 1984 to Jun 2017), and log difference in the Internet search volume intensity on topic "climate change" (from Feb 2004 to Dec 2019). Panel B reports the correlation coefficients between these indexes and common risk factors based on their overlapping time series. The risk factors include market (MKT), size (SMB), value (HML), and momentum (UMD) factors.

Panel A: Summary statistics

	Mean	STD	P10	P25	P50	P75	P90
CH Climate News Innovations	0.000	0.074	–0.066	–0.036	–0.009	0.027	0.082
WSJ Climate News Innovations	0.000	0.157	–0.137	–0.088	–0.031	0.061	0.174
Google SVI Changes	0.009	0.287	–0.318	–0.194	0.019	0.175	0.318

Panel B: Correlations

	CH	WSJ	SVI	MKT	SMB	HML	UMD
CH Climate News Innovations	1.00						
WSJ Climate News Innovations	0.49	1.00					
Google SVI Changes	0.42	0.20	1.00				
MKT	–0.01	0.04	–0.02	1.00			
SMB	0.10	0.04	–0.07	0.33	1.00		
HML	0.09	0.07	0.06	0.33	0.19	1.00	
UMD	0.03	–0.01	–0.01	–0.36	–0.17	–0.43	1.00

Table 4.3: Climate beta and mutual fund performance: Portfolio sorts

The table reports average portfolio gross-of-fee and risk-adjusted returns (in percentages) sorted by fund-level climate beta. Climate beta ($\beta_{Fund}^{Climate}$) is estimated from a regression of mutual fund excess returns on innovations in the CH negative sentiment climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from Jun 2010 to May 2018, we sort funds into quintiles according to their climate betas. Quintile 1 (5) consists of funds with the lowest (highest) climate betas. We report the next month's average of gross returns (both equal-weight and value-weight) within each quintile and the average return difference between the fifth and the first quintiles (the time series of returns for each quintile from Jul 2010 to Jun 2018). For risk-adjusted returns, we use the one-factor model of CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the four-factor model augmented with Pastor and Stambaugh (2003) liquidity factor. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

		Equal-Weight (%)					Value-Weight (%)				
	$\beta_{Fund}^{Climate}$	Ret	CAPM α	FF α	FFC α	FFCPS α	Ret	CAPM α	FF α	FFC α	FFCPS α
Q1	–0.57	1.08	–0.23	–0.19	–0.19	–0.20	1.15	–0.15	–0.14	–0.15	–0.17
		(3.21)	(–2.63)	(–3.87)	(–3.84)	(–3.47)	(3.57)	(–1.60)	(–2.01)	(–2.22)	(–2.21)
Q2	–0.12	1.13	–0.11	–0.08	–0.09	–0.09	1.14	–0.09	–0.08	–0.09	–0.08
		(3.54)	(–1.72)	(–1.89)	(–2.03)	(–1.78)	(3.69)	(–1.33)	(–1.55)	(–1.59)	(–1.35)
Q3	0.10	1.17	–0.11	–0.07	–0.07	–0.07	1.18	–0.06	–0.06	–0.06	–0.05
		(3.60)	(–1.87)	(–1.87)	(–1.84)	(–1.54)	(3.83)	(–1.36)	(–1.32)	(–1.23)	(–0.99)
Q4	0.34	1.22	–0.09	–0.04	–0.04	–0.03	1.20	–0.08	–0.07	–0.05	–0.07
		(3.68)	(–1.37)	(–1.08)	(–0.91)	(–0.72)	(3.83)	(–1.29)	(–1.27)	(–0.99)	(–1.09)
Q5	0.79	1.29	–0.05	0.00	0.02	0.03	1.34	0.04	0.04	0.06	0.08
		(3.73)	(–0.56)	(0.04)	(0.32)	(0.52)	(4.16)	(0.58)	(0.61)	(0.98)	(1.25)
Q5–Q1	1.36	0.21***	0.18***	0.19***	0.21***	0.24***	0.19*	0.19*	0.18*	0.22**	0.26***
		(3.14)	(2.76)	(3.04)	(3.45)	(3.72)	(1.81)	(1.78)	(1.93)	(2.50)	(2.89)

Table 4.4: Cross-sectional regressions of fund performance on fund climate beta

The table reports results from Fama-MacBeth (1973) cross-sectional regressions of mutual fund excess returns, as well as alphas, in month $t+1$ (in percentages) on fund-level climate betas and other control variables measured at the end of month t. Climate beta ($\beta_{Fund}^{Climate}$) is estimated from a regression of mutual fund excess returns on innovations in the CH negative sentiment climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. The control variables include fund size, fund flow, expense ratio, turnover ratio, fund age, manager tenure, tracking error, R-squared, past alpha, and fund style dummies. All independent variables, except dummy variable, are winsorized each month at the 0.5% level. A detailed definition of these variables is provided in Appendix C. The sample period spans from Jul 2010 to Jun 2018. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Gross return			FFC α	FFCPS α
	(1)	(2)	(3)	(4)	(5)
$\beta_{Fund}^{Climate}$	0.188***	0.116**	0.125**	0.070*	0.097**
	(3.13)	(2.30)	(2.53)	(1.78)	(2.00)
Log(TNA)		–0.004	–0.002	0.000	0.000
		(–0.72)	(–0.43)	(–0.04)	(0.06)
Lag Flow		–0.087	–0.087	–0.251	–0.211
		(–0.47)	(–0.53)	(–1.15)	(–0.99)
Expense ratio		–4.849	–5.036**	–1.758	–1.425
		(–1.28)	(–2.09)	(–0.79)	(–0.62)
Turnover		–0.038	–0.034	–0.044**	–0.046**
		(–1.65)	(–1.56)	(–2.21)	(–2.34)
Log(Fund Age)		0.024	0.026	–0.007	–0.009
		(1.38)	(1.46)	(–0.53)	(–0.62)
Log(Tenure)		–0.038***	–0.038***	–0.015	–0.014
		(–2.78)	(–2.97)	(–1.62)	(–1.49)
Tracking Error		0.257	0.187	–0.172**	–0.174**
		(1.27)	(1.17)	(–2.04)	(–2.07)
R-Squared		2.568	1.956	–1.780***	–1.646***
		(1.58)	(1.47)	(–3.53)	(–3.19)
Past Alpha		0.215***	0.210***	0.293***	0.285***
		(3.17)	(3.04)	(4.21)	(4.06)
Constant	1.159***	–1.338	–1.077	1.816***	1.696***
	(3.59)	(–0.91)	(–0.93)	(3.65)	(3.31)
Style dummy	No	No	Yes	Yes	Yes
Adjusted R2	0.023	0.184	0.301	0.146	0.147

Table 4.5: Results from innovations in the WSJ climate change news index

The table reports results of portfolio sorts based on fund-level climate beta with respect to innovations in the WSJ climate change news index over three sample periods: Feb 1986 – Jul 2017 (full sample), Feb 1986 – Dec 1999 (first period), and Jan 2000 – Jul 2017 (recent period). In each month and for each mutual fund, climate beta is estimated from a regression of mutual fund excess returns on innovations in the WSJ climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month, we sort funds into quintiles according to their climate betas. We report the next month's average of gross returns (both equal-weight and value-weight) within each quintile and the average return difference between the fifth and the first quintiles. For risk-adjusted returns, we report the difference in alpha between the two extreme quintiles using the four-factor model of Carhart (1997), and the four-factor model augmented with Pastor and Stambaugh (2003) liquidity factor. Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Feb 1986 – Jul 2017		Feb 1986 – Dec 1999		Jan 2000 – Jul 2017	
	EW	VW	EW	VW	EW	VW
Q1	0.94	0.94	1.43	1.44	0.54	0.48
	(2.57)	(3.51)	(2.52)	(3.66)	(1.16)	(1.34)
Q2	0.93	0.88	1.36	1.34	0.61	0.50
	(2.75)	(3.60)	(2.55)	(3.69)	(1.43)	(1.50)
Q3	0.94	0.91	1.38	1.36	0.62	0.53
	(2.84)	(3.73)	(2.68)	(3.89)	(1.47)	(1.55)
Q4	0.99	1.00	1.40	1.41	0.70	0.63
	(3.01)	(3.96)	(2.70)	(3.88)	(1.70)	(1.85)
Q5	1.08	1.04	1.38	1.41	0.79	0.72
	(3.09)	(3.92)	(2.46)	(3.80)	(1.85)	(1.97)
Q5–Q1	0.14**	0.11	–0.05	–0.03	0.25***	0.25***
	(2.15)	(1.48)	(–0.61)	(–0.33)	(2.82)	(2.65)
FFC α	0.11	0.07	–0.07	–0.04	0.22**	0.21**
	(1.63)	(0.93)	(–0.92)	(–0.49)	(2.52)	(2.24)
FFCPS α	0.11	0.07	–0.06	–0.03	0.22**	0.21**
	(1.64)	(0.93)	(–0.73)	(–0.33)	(2.54)	(2.25)

Table 4.6: Climate beta and mutual fund performance: Portfolio sorts based on net-of-fee returns

The table reports average portfolio net-of-fee and risk-adjusted returns (in percentages) sorted by fund-level climate beta. Climate beta ($\beta_{Fund}^{Climate}$) is estimated from a regression of mutual fund excess returns on innovations in the CH negative sentiment climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from Jun 2010 to May 2018, we sort funds into quintiles according to their climate betas. Quintile 1 (5) consists of funds with the lowest (highest) climate betas. We report the next month's average of net-of-fee returns (both equal-weight and value-weight) within each quintile and the average net return difference between the top and bottom quintiles (the time series of returns for each quintile from Jul 2010 to Jun 2018). For risk-adjusted returns, we use the one-factor model of CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the four-factor model augmented with Pastor and Stambaugh (2003) liquidity factor. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Equal-Weight (%)					Value-Weight (%)				
	Ret	CAPM α	FF α	FFC α	FFCPS α	Ret	CAPM α	FF α	FFC α	FFCPS α
Q1	1.00	–0.31	–0.26	–0.27	–0.28	1.08	–0.22	–0.21	–0.22	–0.24
	(2.98)	(–3.52)	(–5.51)	(–5.40)	(–4.80)	(3.36)	(–2.37)	(–3.00)	(–3.24)	(–3.11)
Q2	1.06	–0.18	–0.15	–0.16	–0.16	1.08	–0.15	–0.14	–0.15	–0.14
	(3.32)	(–2.78)	(–3.57)	(–3.68)	(–3.25)	(3.50)	(–2.20)	(–2.64)	(–2.65)	(–2.32)
Q3	1.09	–0.18	–0.14	–0.14	–0.14	1.12	–0.13	–0.12	–0.12	–0.11
	(3.37)	(–3.08)	(–3.77)	(–3.70)	(–3.16)	(3.63)	(–2.63)	(–2.77)	(–2.59)	(–2.15)
Q4	1.14	–0.16	–0.12	–0.11	–0.11	1.14	–0.14	–0.13	–0.12	–0.13
	(3.45)	(–2.56)	(–2.90)	(–2.72)	(–2.30)	(3.62)	(–2.40)	(–2.51)	(–2.18)	(–2.19)
Q5	1.21	–0.13	–0.08	–0.06	–0.05	1.27	–0.03	–0.03	–0.01	0.01
	(3.49)	(–1.56)	(–1.30)	(–1.05)	(–0.83)	(3.94)	(–0.35)	(–0.39)	(–0.09)	(0.19)
Q5–Q1	0.21***	0.18***	0.18***	0.21***	0.23***	0.19*	0.19*	0.18*	0.22**	0.26***
	(3.06)	(2.68)	(2.96)	(3.37)	(3.63)	(1.80)	(1.77)	(1.92)	(2.49)	(2.87)

Table 4.7: Stock-level climate beta and expected stock returns: Portfolio sorts

Panel A reports average stock portfolio excess returns and alphas (in percentages) sorted by stock-level climate betas. Stock-level climate beta ($\beta_{Stock}^{Climate}$) is estimated from a regression of stock excess returns on innovations in the CH negative sentiment climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing stock returns. At the end of each month from Jun 2010 to May 2018, we sort stocks into quintiles according to their stock-level climate betas. We report the next month's average returns (both equal-weight and value-weight) within each stock quintile and the average return difference between the top and bottom quintiles (the time series of returns for each quintile from Jul 2010 to Jun 2018). For risk-adjusted returns, we use the four-factor model of Carhart (1997) and the five-factor model of Fama and French (2015) augmented with the momentum factor. Panel B examines the characteristics of stock-level climate beta by performing a series of Fama-MacBeth (1973) cross-sectional regressions of stock-level climate beta in month t on various stock characteristics and alternative measures of climate risk exposures in the same month. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Stock-level climate beta and expected returns

	Equal-Weight (%)			Value-Weight (%)		
Portfolio	Ret	FFC α	FF6 α	Ret	FFC α	FF6 α
Q1	1.13	–0.08	–0.06	1.16	–0.16	–0.12
	(2.69)	(–0.84)	(–0.66)	(3.00)	(–1.32)	(–0.97)
Q2	1.36	0.21	0.21	1.30	0.01	0.00
	(3.86)	(4.74)	(4.54)	(3.92)	(0.10)	(–0.07)
Q3	1.42	0.29	0.28	1.21	–0.03	–0.05
	(4.14)	(6.66)	(6.08)	(3.65)	(–0.35)	(–0.60)
Q4	1.43	0.27	0.26	1.36	0.13	0.12
	(4.00)	(4.88)	(5.36)	(4.23)	(1.59)	(1.48)
Q5	1.49	0.20	0.23	1.45	0.11	0.14
	(3.38)	(2.32)	(2.74)	(3.65)	(1.01)	(1.40)
Q5–Q1	0.36***	0.28**	0.29**	0.29**	0.27**	0.26*
	(2.97)	(2.29)	(2.32)	(2.22)	(2.12)	(1.85)

Panel B: Characteristics of stock climate beta

Dependent variable: $\beta_{Stock}^{Climate}$	(1)	(2)	(3)	(4)	(5)
Constant	–0.183***	–0.185***	–0.184***	–0.133***	–0.139***
	(–4.57)	(–4.37)	(–4.54)	(–3.10)	(–3.20)
Market beta	0.037***	0.037***	0.037***	0.032***	0.034***
	(3.25)	(3.25)	(3.24)	(2.78)	(2.97)
Log(Size)	0.010***	0.010***	0.010***	0.007***	0.007***
	(5.14)	(4.73)	(5.14)	(3.98)	(3.88)
BM	–0.030***	–0.030***	–0.030***	–0.029***	–0.031***
	(–3.04)	(–3.02)	(–3.06)	(–2.62)	(–2.79)
Mom	–0.072	–0.071	–0.071	–0.069	–0.069
	(–1.57)	(–1.57)	(–1.57)	(–1.50)	(–1.51)
Rev	0.016	0.016	0.016	0.020	0.021
	(0.13)	(0.13)	(0.13)	(0.17)	(0.18)

Inst Own	0.034***	0.034***	0.034***	0.036***	0.040***
	(3.83)	(3.79)	(3.84)	(3.43)	(3.75)
Leverage	–0.023*	–0.023*	–0.023*	–0.024**	–0.029**
	(–1.83)	(–1.81)	(–1.84)	(–2.03)	(–2.57)
R&D	0.002***	0.002***	0.002***	0.003**	0.003**
	(2.63)	(2.64)	(2.63)	(2.56)	(2.56)
E-Score		–0.367			
		(–0.77)			
∆E-Score			0.034**		
			(2.15)		
Climate exposure				–0.009***	
				(–3.23)	
Climate risk					–0.003*
					(–1.89)
Climate Sentiment					–0.003
					(–1.47)
Adjusted R2	0.080	0.080	0.080	0.082	0.080

Table 4.8: Drivers of the stock-level climate beta – stock return relation: Cross-sectional regressions

The table reports regression results for the possible drivers of the stock-level climate beta and stock return relation. The dependent variables are change in institutional ownership (in percent, led by three months) in Specifications (1), price pressure defined as the elasticity of demand (Koijen and Yogo, 2019) times the change in institutional ownership (led by three months) in Specification (2), average gross profit over asset (over the next twelve months) in Specification (3), average return on equity (over the next twelve months) in Specification (4), and average return on asset (over the next twelve months) in Specification (5). The main independent variable is stock-level climate betas. The sample period spans from Jun 2010 to May 2018. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Investor channel		Financial performance channel		
Dependent Variable	(1) Δ Inst Own [t+3]	(2) Price Pressure [t+3]	(3) Gross Profit [t+12]	(4) ROE [t+12]	(5) ROA [t+12]
$\beta_{Stock}^{Climate}$	0.166**	0.316**	0.005***	0.064*	0.004***
	(2.37)	(2.09)	(2.61)	(1.81)	(3.66)
Market beta	–0.002	–0.004	–0.001**	0.010	–0.004***
	(–1.47)	(–1.37)	(–2.07)	(0.58)	(–8.05)
Log(Size)	–0.001***	–0.004*	0.000*	–0.013	0.003***
	(–2.96)	(–1.74)	(–1.85)	(–0.82)	(11.66)
BM	–0.001	–0.003*	–0.005***	–0.006	0.001**
	(–1.55)	(–1.70)	(–6.14)	(–0.42)	(2.08)
Mom	0.011***	0.023***	0.007***	0.070***	0.015***
	(10.80)	(7.20)	(4.98)	(3.47)	(10.21)
Rev	0.026***	0.050***	0.027***	0.210	0.036***
	(6.50)	(6.42)	(7.51)	(1.58)	(12.97)
Gross Profit			0.948***		
			(150.92)		
ROE				1.252***	
				(4.46)	
ROA					0.919***
					(113.22)
Constant	0.015***	0.046**	0.023***	0.173	–0.035***
	(4.31)	(2.20)	(4.67)	(0.82)	(–11.60)
Adjusted R2	0.010	0.008	0.940	0.589	0.890

Table 4.9: Fund-level climate beta and $Flows\_Climate$

The table reports the average $Flows\_Climate$ in each quintile sorted by mutual fund climate betas. Each quarter, we sort mutual funds into quintiles based on their fund-level climate betas and within these quintiles, we compute the mean values of $Flows\_Climate$. We report, for each quintile, the time-series average of the quarterly mean values of $Flows\_Climate$. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Sorted by $\beta_{Fund}^{Climate}$	$Flows\_Climate$
Q1	–0.50
Q2	–0.07
Q3	0.02
Q4	0.12
Q5	0.31
Q5-Q1	0.81***
	(3.25)

Table 4.10: Performance of funds holding high versus low climate beta stocks: Portfolio sorts

The table reports results of portfolio sorts based on fund-level score of climate beta stock holdings. The score is calculated as the investment-weighted stock-level climate betas using quarterly stock holdings from Thomson Financial Mutual Fund Holdings database. At the end of each month from Jun 2010 to May 2018, we sort funds into quintiles according to their fund-level score of climate beta stock holdings. We report the next month's average of gross returns (both equal-weight and value-weight) within each quintile and the average return difference between the top and bottom quintiles (the time series of returns for each quintile from Jul 2010 to Jun 2018). For risk-adjusted returns, we use the one-factor model of CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the four-factor model augmented with Pastor and Stambaugh (2003) liquidity factor. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Equal-Weight (%)					Value-Weight (%)				
Portfolio	Ret	CAPM α	FF α	FFC α	FFCPS α	Ret	CAPM α	FF α	FFC α	FFCPS α
Q1	1.12	–0.21	–0.16	–0.17	–0.14	1.15	–0.14	–0.15	–0.15	–0.11
	(3.28)	(–2.25)	(–2.75)	(–2.81)	(–3.23)	(3.60)	(–1.62)	(–2.07)	(–2.05)	(–2.05)
Q2	1.16	–0.13	–0.09	–0.09	–0.08	1.17	–0.08	–0.08	–0.08	–0.05
	(3.58)	(–2.10)	(–2.33)	(–2.29)	(–2.39)	(3.81)	(–1.26)	(–1.42)	(–1.35)	(–1.01)
Q3	1.21	–0.09	–0.05	–0.05	–0.04	1.27	0.00	0.01	0.02	0.04
	(3.67)	(–1.59)	(–1.48)	(–1.48)	(–1.34)	(4.00)	(–0.04)	(0.27)	(0.55)	(0.98)
Q4	1.25	–0.07	–0.03	–0.02	–0.02	1.26	–0.04	–0.03	–0.03	0.00
	(3.70)	(–1.04)	(–0.60)	(–0.55)	(–0.40)	(3.93)	(–0.61)	(–0.58)	(–0.48)	(–0.01)
Q5	1.31	–0.03	0.03	0.04	0.04	1.37	0.06	0.07	0.08	0.09
	(3.74)	(–0.38)	(0.49)	(0.70)	(0.81)	(4.13)	(0.79)	(1.14)	(1.34)	(1.63)
Q5–Q1	0.19***	0.18**	0.19***	0.21***	0.19***	0.23**	0.20**	0.22**	0.23***	0.20**
	(2.67)	(2.40)	(2.67)	(2.97)	(3.14)	(2.30)	(2.12)	(2.50)	(2.75)	(2.56)

Table 4.11: Do high climate beta funds outperform by holding high climate beta stocks?

The table reports results for the time-series regressions of return spreads between high and low climate beta fund quintiles (as in Table 4.3) on returns spreads between high and low fund quintiles sorted by fund-level score of climate beta stock holdings (as in Table 4.10). We control for standard risk factors, including market, size, value, and momentum factors. We present results for both equal-weighted and value-weighted fund portfolios. The sample period spans from Jul 2010 to Jun 2018. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Dependent Var	Q5–Q1 EW return spread (Table 4.3)				Q5–Q1 VW return spread (Table 4.3)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant (Alpha)	0.21***	0.21***	0.08*	0.07	0.19*	0.22**	0.01	0.01
	(3.14)	(3.45)	(1.88)	(1.42)	(1.81)	(2.50)	(0.17)	(0.19)
Q5–Q1 return spread (Table 4.10)			0.67***	0.68***			0.94***	0.97***
			(8.29)	(8.36)			(6.17)	(6.97)
MKT		0.02		0.02**		0.00		0.01
		(1.00)		(2.07)		(0.14)		(0.53)
SMB		–0.03		–0.06**		–0.08		–0.13***
		(–0.83)		(–1.97)		(–1.48)		(–2.70)
HML		0.02		0.02		0.01		0.01
		(0.42)		(0.62)		(0.18)		(0.28)
UMD		–0.05*		–0.02		–0.07		–0.03
		(–1.75)		(–1.13)		(–1.55)		(–1.05)
Observations	96	96	96	96	96	96	96	96
Adjusted R2	0.00	0.04	0.49	0.54	0.00	0.04	0.44	0.51

Chapter 5

Conclusion

5.1. Summary and implications

Overall, this thesis mainly lies in the area of empirical asset pricing, focusing on institutional investors, option markets, and sustainable finance.

More specifically, in Chapter 2, we contribute to the hedge fund performance literature by showing that exposure of hedge funds to H-Bear factor can explain a large proportion of the cross-sectional variation in their returns. We challenge the conventional wisdom which associates the returns of insurance-like hedge fund strategies with realized market tail risk. We show that hedge fund that buy (sell) Bear can be seen as the outcome of combination of unhedged market exposure and long (short) H-Bear exposure. Furthermore, both buyers and sellers have positive and almost identical unhedged market exposure, suggesting that both are exposed to similar market downside risk. Hence, the systematic difference in the expected returns of high versus low H-Bear beta funds arises as a natural outcome of their differential exposure to the H-Bear returns, which reflect a bear risk premium being paid to hedge the change in concerns of a future market crash, as opposed to and on top of the ex-post downside risk. Consistent with our risk-based explanation, low H-Bear exposure funds outperform high H-Bear exposure funds even during market crashes or tail events (i.e., defined as bad times in the literature) but underperform when bear market risk materializes. Overall, our measure contributes to a new risk dimension that affects hedge fund performance and we show that such risk factor is distinct from the popular ex-post tail risk premium documented in the existing literature.

In Chapter 3, building on a theoretical framework in which investors demand a risk premium as a compensation for political uncertainty, we document lower delta-hedged option returns for high-political risk firms using a newly developed text-based measure of firm-level political risk. The effect holds both in a cross-sectional and in a time-series context. The findings suggest that investors are willing to pay a higher option premium for firms that have higher exposure to political shocks. We show that the pricing effect comes from both demand and supply sides as well as the rational incorporation of political risk in the stochastic discount factor. In this respect, we document that the effect of political risk on option returns is more pronounced among firms with high option demand pressure, high information asymmetry and high default risk. Importantly, we dissect the demand pressure arising from different investor groups. Our evidence demonstrates that firm-level political risk is associated with higher speculative call demand stemming from public customers and higher hedging put demand stemming from firm proprietary traders. Hence, it appears that due to its heterogeneous nature firm-level political risk is treated differently by different investor groups. Overall, our evidence underlines the multifaceted nature of political risk at the firm level.

Chapter 4 studies the effect of climate change concern on mutual fund performance. We use fund-level climate beta, i.e., the sensitivity of each mutual fund returns to innovations in climate change news index, to capture the fund's ability to hedge against climate change and document that high climate beta funds outperform low climate beta funds both in raw and risk-adjusted return basis. The outperformance stems from funds tilting their portfolios towards high climate beta stocks, i.e., stocks with better climate-hedging potential. We verify the characteristics of these stocks by documenting that they are related to the improvement in firms' environmental performance. Consistent with the strengthened environmental concerns over the recent period that drive customers' demand for sustainable products and investors' demand for sustainable holdings, these "climate-hedged" stocks perform better on average. Hence, funds overweighting these stocks in their portfolios benefit from such price appreciation. Overall, we conclude that the integration of climate concern into investment processes can be motivated by financial performance.

5.2. Limitations and future research

Despite the thorough analysis conducted in previous chapters and respective appendices, additional investigation may shed more light to the empirical findings of the thesis. Such a supplementary analysis can examine further the robustness of our results as well as provide a deeper understanding of the main conclusion drawn. In this respect, some of the issues discussed below can serve as ideas for future research.

Chapter 2 documents that exposure to H-Bear factor, the return of a bear spread portfolio hedged with respect to the market return, can explain the cross-section of hedge fund returns. However, there are several issues associated with the analysis. First, due to data limitation, the main analysis in this chapter solely applies historical hedge fund data from the Hedge Fund Research database. While the coverage of 11,084 unique hedge funds is sufficiently large and we indeed provide robustness tests with a shorter sample period using EurekaHedge and Lipper TASS databases, it is a common practice in the literature to combine several hedge fund databases to mitigate the self-selection bias. Joenväärä, Kauppila, Kosowski, and Tolonen (2021) document that using a merged hedge fund database significantly alters the importance of various predictors of hedge fund performance. Second, the Covid-Crash (and recovery) might be an interesting time period to study in the context of bear market risk. A sub-analysis would be to examine the association between bear market risk and hedge fund performance during the most severe market crashes in the past 20 years, the “Lehman Bankruptcy” crash in 2008 and the coronavirus crash in 2020. Hence, it would be interesting to extend the sample period to include this event in our analysis. Third, although we conceptually point out that H-Bear exposure stems from hedge funds trading bear beta stocks as well as their strategies that resemble buying or selling insurance, we need a closer look at disclosed holdings positions of hedge fund firms to further understand the channels. However, we note that disclosed option holdings of hedge funds are limited and thus, we leave this investigation for future research.

In Chapter 3, we perform a comprehensive empirical analysis to show that high political-risk firms exhibit delta-hedged option returns that are significantly lower than those of low-political risk firms. In other words, firm-level political risk is priced in the equity option market. While we examine the economic mechanism through its impact on the demand and supply side of the option market, one concern is the need to develop a rational theoretical model that motivates the negative relation between firm-level political risk and option returns. For example, a firm's profitability follows a stochastic process and can be affected by firm-level political uncertainty. We can follow this direction to link how the perceived uncertainty about the firm's profits caused by political risk can affect volatility risk premium and in turn option returns. Also, it would be interesting to identify several other exogenous shocks to study the effect of an increase in firm-level political risk on option returns. One example is the redrawing of electoral districts. The redistricting followed the decennial census of 2010 and changed many firms' exposure to Congress by placing them in a new district with the potential to have a new House representative. We can investigate whether the change in such firm-level political risk translates into change in option returns after the event and which economic channels lead to the impact, e.g., change in option demand and change in the analyst forecast dispersion. We would like to explore such event studies in the future.

Finally, in Chapter 4, we show that high climate beta mutual funds outperform low climate beta mutual funds. One implicit assumption in our study is that climate beta directly reflects the ability of mutual funds to hedge against climate change concerns. However, it is possible that the positive covariance between the returns of funds and the climate change concern index does not necessarily mean that these funds are actively hedging against climate risks. It can be a result of omitted variable bias. Therefore, we might need to dig further and study the characteristics of climate-hedging mutual funds to see whether these funds are marketed themselves as ESG funds or whether they are committed to taking climate actions in their investments. Moreover, one possible direction for future research is to examine whether high climate beta mutual funds are skilled at exploiting the climate change concern. Given the high disagreement of ESG ratings among different data providers, the ability to identify good ESG firms that have greater green technology, growing sales and positive unexpected profitability is a valuable skill. We can examine whether high mutual fund climate beta is associated with other existing measures of mutual fund skills such as mutual fund R2 or active weight and whether they tilt their portfolios toward good E stocks proxied by material E-score or green patents. Also, whether high climate beta mutual funds outperform their peers by possessing skills of timing climate change concern is an interesting question for future study.

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Appendix A

Appendix to Chapter 2

A1. Definition of variables for Chapter 2

For each fund i at the end of month t, we compute all variables used to predict fund returns in month $t+1$. This appendix provides detailed definition of all variables in the paper. Note that for all variables computed using the past 24 months of hedge fund return series, we require at least 18 months of non-missing returns.

A1.1. Time-varying fund exposures and characteristics

- $\boldsymbol{\beta^{H-BEAR}}$ **or H-Bear beta**: is the coefficient $\beta_{i,t}^{H-BEAR}$ obtained by regressing monthly hedge fund excess returns on the market excess returns and the Bear portfolio excess returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t} \times MKT_t + \beta_{i,t}^{H-BEAR} \times r_{Bear,t} + \epsilon_{i,t}$ over a 24-month rolling-window period. Details of the Bear portfolio construction is provided in Section 2.
- $\boldsymbol{\beta^{MKT}}$: is the coefficient $\beta_{i,t}^{MKT}$ from the regression of monthly hedge fund excess returns on the market excess returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \epsilon_{i,t}$ over the past 24 months.
- $\boldsymbol{\beta^{\Delta VOL}}$***,*** $\boldsymbol{\beta^{\Delta SKEW}}$***, and*** $\boldsymbol{\beta^{\Delta KURT}}$(Agarwal, Bakshi, and Huij, 2010): are exposures to higher risk-neutral moments obtained by regressing monthly hedge fund excess returns on the market excess returns and ΔVOL_t, $\Delta SKEW_t$, and $\Delta KURT_t$ (monthly relative changes in the market volatility, skewness, and kurtosis respectively) over a 24-month rolling-window period: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{\Delta VOL} \times \Delta VOL_t + \beta_{i,t}^{\Delta SKEW} \times \Delta SKEW_t + \beta_{i,t}^{\Delta KURT} \times \Delta KURT_t + \epsilon_{i,t}$. Market volatility, skewness, and kurtosis are the Bakshi, Kapadia, and Madan (2003) model-free estimate of risk-neutral higher moments of market log return spanning the period up to option maturity day. They are extracted from S&P 500 index options using trapezoidal approximation and are linearly interpolated to have the measures with constant 30-day maturity.
- **TailRisk** (Agarwal, Ruenzi, and Weigert, 2017): is defined as the lower tail dependence of hedge fund returns and the market returns over the past 24 months ($TailSens_{i,t}$), multiplied by the ratio of the absolute value of their respective expected shortfalls over the same period with the cutoff of q = 5%. $TailSens_{i,t}$ of fund i takes the value of zero, 0.5, or 1 if none, one, or both of the fund's two worst return realizations occur at the same time of the market's two worst monthly returns over the past 24 months.
- $\boldsymbol{\beta^{UNC}}$ (Bali, Brown, and Caglayan, 2014): is hedge fund exposure to macroeconomic uncertainty, $\beta_{i,t}^{UNC}$, from the regression of monthly hedge fund excess returns on the economic uncertainty index: $r_{i,t} = \alpha_{i,t} +$

$\beta_{i,t}^{UNC} \times UNC_t + \epsilon_{i,t}$ over the past 24 months. The monthly economic uncertainty index is provided on Bali's personal website.

- $\boldsymbol{\beta^{RIX}}$ (Gao, Gao, and Song, 2018): is interpreted as skills at exploiting rare disaster concern, which is the coefficient, $\beta_{i,t}^{RIX}$, from the regression of monthly hedge fund excess returns on the market excess returns and the rare disaster concern index (RIX) over the past 24 months: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{RIX} \times RIX_t + \epsilon_{i,t}$. Data for RIX is obtained from Gao's website and covers the period over 1996–2011.
- $\boldsymbol{\beta^{RETRIX}}$: is the coefficient on RETRIX obtained by regressing monthly hedge fund excess returns on the market excess returns and the Investable RIX factor (RETRIX) over the rolling 24-month window period: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{RETRIX} \times RETRIX_t + \epsilon_{i,t}$. Monthly Investable RIX factor is computed as follows. We modify the formula for RIX slightly to allow the use of available option quotes.

$$RIX = V^- - IV^- = \frac{2e^{r\tau}}{\tau}\int_{K<S_t}^{\cdot} \frac{ln(S_t/K)}{K^2}\, P(S_t;K,T)dK$$
$$\approx \frac{2e^{r\tau}}{\tau}\sum_{i=1}^{n_P} \frac{ln(S_t/K_i^P)}{(K_i^P)^2} P(S_t;K_i^P,T)\Delta K_i^P$$

where $\tau \equiv T - t$ is the time to maturity, r is the risk-free rate, S_t is the spot price, n_P is the number of OTM puts with available price data, i indexes the OTM puts, K_i^P is the strike of ith OTM put option when the strikes are ordered in decreasing order, and $P(S_t;K_i^P,T)$ is price of the put with strike K_i^P maturing at T. $\Delta K_1^P = S - K_1^P$ and $\Delta K_i^P = K_{i-1}^P - K_i^P$ for $2 \le i \le n^P$. For constructing RETRIX, each day, we follow the formula to form the option position using all valid OTM put options on the S&P 500 index that expire on the third Friday of the next calendar month. The option position is hold for one day to calculate the return. We then take the average of the daily option position returns within a month to calculate monthly RETRIX.

- **R2** (Titman and Tiu, 2011): is the R^2 measure of a fund from the regression of monthly hedge fund excess returns on the Fung and Hsieh (2004) seven factors over the past 24 months.
- **SDI** (Sun, Wang, and Zheng, 2012): is strategy distinctiveness for a fund calculated as one minus the correlation between the fund returns and the average returns of funds with the same investment style based on the past 24 months.
- **Downside Return** (Sun, Wang, and Zheng, 2018): is computed as the time-series average of fund i returns during months in which aggregate hedge funds returns are below the median level over the past 24 months.
- **Age**: is the age of hedge fund i since its inception (measured in years)
- **Size**: is computed as natural log of asset under management (in $ million) of hedge fund i in month t.
- **Ret VOL, SKEW, KURT**: are respectively the standard deviation, skewness, and kurtosis of fund i monthly returns over the past 24 months.
- **Past return (12M)**: is the cumulative return of fund i over the past 12 months ending in month t.

A1.2. Time-invariant fund characteristics

- **Min Investment**: is computed as the natural log of (1 + minimum investment amount).
- **Management Fee**: is the annual management fee (in percentage) for hedge fund i.
- **Incentive Fee**: is the annual incentive fee (in percentage) for hedge fund i.
- **Lock Up**: is the minimum length of time (measured in months) that investors are required to keep their money invested in fund i.
- **Redemption**: is the length of advanced notice that hedge fund i requires from investors who wish to redeem their shares.

- **Leverage**: is an indicator variable that takes the value of one if hedge fund i uses leverage.
- **Hurdle**: is an indicator variable that takes the value of one if hedge fund i uses a hurdle rate.
- **HWM**: is an indicator variable that takes the value of one if hedge fund i use high watermark.
- **Offshore**: is an indicator variable that takes the value of one if hedge fund i is based in offshore location outside of the USA.

A1.3. Hedge fund risk factors

- **PTFSBD**: Monthly return on trend-following risk factor in bonds
- **PTFSFX**: Monthly return on trend-following risk factor in currencies.
- **PTFSCOM**: Monthly return on trend-following risk factor in commodities.
- **S&P**: The S&P 500 index monthly total return.
- **SCMLC**: The size spread factor, computed as the difference between the Russell 2000 index monthly return and the S&P 500 monthly return.
- **BD10RET**: The bond market factor, computed as the monthly change in the 10-year treasury maturity yield.
- **BAAMTSY**: The credit spread factor, computed as the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.

A2. Additional results for Chapter 2

Table A2.1: Correlations between hedge fund characteristics

The table reports correlations between different hedge fund characteristics. Definitions of these hedge fund characteristics are provided in Appendix A1. We report the cross-sectional correlations between time-invariant hedge fund characteristics, while reporting the time-series averages of the monthly cross-sectional correlations between time-variant hedge fund characteristics. Our sample covers hedge funds from the HFR database over the period from January 1996 to December 2017.

	Size	Age	Min Inv	Mnt Fee	Inc Fee	Lock Up	Re-deem	Lev-erage	Hur-dle	HWM	Off-shore
Size	1.00										
Age	0.29	1.00									
Min Investment	0.15	0.01	1.00								
Management Fee	–0.04	–0.07	0.01	1.00							
Incentive Fee	–0.08	–0.08	0.23	0.24	1.00						
Lock Up	0.00	–0.01	0.18	–0.02	0.09	1.00					
Redemption	0.15	0.02	0.23	–0.01	0.01	0.32	1.00				
Leverage	–0.03	–0.04	0.06	0.09	0.25	–0.02	–0.05	1.00			
Hurdle	0.01	0.01	–0.01	–0.10	0.02	0.05	0.05	–0.09	1.00		
HWM	–0.02	–0.08	0.23	0.14	0.56	0.10	0.16	0.16	0.01	1.00	
Offshore	0.17	–0.12	–0.08	0.09	–0.04	–0.18	–0.03	0.00	0.05	0.07	1.00

Table A2.2: Persistence of H-Bear factor exposure

The table reports the persistence of H-Bear beta. At the end of each month, we sort hedge funds into H-Bear beta quintile portfolios and calculate the average H-Bear beta for each quintile during the subsequent portfolio holding period of 1 month, 3 months, and up to 36 months. A quintile's H-Bear beta is the cross-sectional average of funds' H-Bear beta in that quintile. We report the time-series mean of the average H-Bear beta of each quintile portfolio for the portfolio formation month and for the subsequent months. We also report the difference in average H-Bear beta between Q5 and Q1. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Q1	Q2	Q3	Q4	Q5	Q5–Q1	t-stat
Portfolio formation	–0.55	–0.14	–0.03	0.10	0.53	1.08***	(13.55)
Holding 1 months	–0.51	–0.13	–0.03	0.09	0.49	1.00***	(13.97)
3 months	–0.47	–0.13	–0.03	0.08	0.46	0.93***	(13.94)
6 months	–0.43	–0.12	–0.03	0.07	0.42	0.84***	(13.87)
9 months	–0.39	–0.11	–0.03	0.06	0.38	0.76***	(13.72)
12 months	–0.35	–0.10	–0.03	0.06	0.34	0.69***	(13.56)
18 months	–0.29	–0.09	–0.03	0.04	0.28	0.56***	(12.99)
24 months	–0.23	–0.08	–0.03	0.03	0.22	0.45***	(12.13)
36 months	–0.17	–0.06	–0.03	0.02	0.14	0.31***	(11.12)

Table A2.3: Performance of H-Bear beta-sorted fund portfolios during market crashes versus normal times
The table reports the average equal-weighted excess returns of hedge fund portfolios sorted with respect to H-Bear beta during periods of market crashes versus normal times. MKT denotes the excess return of the market. In Specification (1), we define the periods of market crashes as months when the excess market returns are lower than the sample period 10^{th} percentile (MKT < P10). Specification (2) presents performance of bear beta quintiles during normal times. Specifications (3) and (4) reports the results when the excess market returns are negative and positive respectively. The sample period is from January 1998 to December 2017. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
(1) MKT < P10						
Equal-weighted return (%)	–1.44	–1.62	–1.90	–2.45	–4.28	–2.85***
	(–2.47)	(–4.85)	(–8.66)	(–12.19)	(–8.77)	(–2.82)
(2) MKT > P10						
Equal-weighted return (%)	1.13	0.80	0.73	0.76	0.80	–0.33***
	(7.06)	(8.42)	(7.48)	(6.61)	(7.13)	(–2.61)
(3) MKT < 0						
Equal-weighted return (%)	–0.62	–0.59	–0.65	–0.90	–1.78	–1.16***
	(–2.26)	(–2.52)	(–2.92)	(–4.26)	(–5.62)	(–3.06)
(4) MKT > 0						
Equal-weighted return (%)	1.78	1.26	1.15	1.25	1.55	–0.23
	(7.09)	(10.24)	(8.09)	(6.41)	(6.67)	(–1.13)

Table A2.4: Put-writing versus put-buying

The table reports the average return difference between two hypothetical funds. Each position is established at the end of month t and is held until the end of month $t+1$ when the portfolio is rebalanced. The portfolio buys (sells) put options at the ask (bid) prevailing at the market close of the month-end trade date.

- Fund A uses a naked put-writing strategy. Following Jurek and Stafford (2015), Fund A's monthly return, $r_{A,t+1}$, is calculated as the change in the value of put option, $P(K(Z),T)$, plus the accrued interest, AI_{t+1}, divided by the portfolio's equity capital, $\kappa_E(L)$:
$$r_{A,t+1} = \left[P_t^{bid}(K(Z),T) - P_{t+1}^{ask}(K(Z),T) + AI_{t+1}\right]/\kappa_E(L)$$
T is the option expiration date. Z is strike level and $K(Z)$ is option strike price corresponding to Z: $K(Z) = S_t \cdot exp(\sigma_{t+1} \cdot Z)$, where S_t is the S&P 500 index and σ_{t+1} is the one-month stock index implied volatility (VIX index) observed at time t. We select the option whose strike is closest to but below the proposal value and whose expiration date is closest to but after the end of the month (around 7 weeks to maturity). L is the portfolio leverage level: $L = \kappa_A/\kappa_E$, where κ_A is the unlevered asset capital: $\kappa_A = e^{-r_{f,t+\tau}} \cdot K(Z) - P_t^{bid}(K(Z),T)$, $r_{f,t+\tau}$ is the risk-free rate corresponding to the time to option expiration. The accrued interest, AI_{t+1}, is calculated as: $AI_{t+1} = \left(\kappa_E(L) + P_t^{bid}(K(Z),T)\right) \cdot (e^{r_{f,t+1}} - 1)$.
- Fund B follows a put-buying strategy and at the same time, invests the remaining capital into the S&P 500 index. Fund B's monthly return, $r_{B,t+1}$, is calculated as the change in the value of put option, $P(K(Z),T)$, minus the interest payment, I_{t+1}, plus the change in value of the investment in S&P 500 index, ΔSP_{t+1}, divided by the portfolio's equity capital, $\kappa_E(L)$:
$$r_{B,t+1} = \left[P_{t+1}^{bid}(K(Z),T) - P_t^{ask}(K(Z),T) - I_{t+1} + \Delta SP_{t+1}\right]/\kappa_E(L)$$
The interest payment, I_{t+1}, is calculated as: $I_{t+1} = (\kappa_A(L) - \kappa_E(L)) \cdot (e^{r_{f,t+1}} - 1)$. The portfolio leverage level: $L = \kappa_A/\kappa_E$, where $\kappa_A = e^{-r_{f,t+\tau}} \cdot K(Z) + P_t^{ask}(K(Z),T)$. The change in value of the investment in S&P 500 index is calculated as: $\Delta SP_{t+1} = \left(\kappa_A - P_t^{ask}(K(Z),T)\right) \cdot (S_{t+1}/S_t - 1)$.

The sample period is from January 1996 to December 2017. Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	For Z = –1 and L = 2		
	Fund A	Fund B	Fund B – Fund A
Returns (%)	1.04***	0.10	–0.94**
	(8.00)	(0.20)	(–2.42)
FH alpha	0.72***	–1.27***	–1.99***
	(7.05)	(–12.95)	(–10.17)
(1) MKT < P10			
Returns (%)	–3.42***	–13.42***	–10.00***
	(–5.47)	(–13.60)	(–9.65)
(2) MKT > P10			
Returns (%)	1.53***	1.57***	0.05
	(17.75)	(4.84)	(0.16)
(3) Residuals(*) < 0			
Returns (%)	–0.45	2.30	2.75**
	(–0.75)	(1.44)	(2.42)
(4) Residuals > 0			
Returns (%)	1.36***	–0.38	–1.74***
	(15.86)	(–0.91)	(–4.58)

(*) Residuals are from the regression of put-writing returns on the market returns over the whole sample period.

Table A2.5: Fama and MacBeth regressions: Controlling for lags of hedge fund returns

The table presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund excess returns in month $t+1$ on H-Bear beta (β^{H-BEAR}) in month t controlling for several lags of hedge fund returns over the sample period from January 1998 to December 2017. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. Return [t], Return [t–1], and Return [t –2] are hedge fund returns in month t, month $t-1$, and month $t-2$ respectively. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Specification	(1)	(2)	(3)
Intercept	0.46***	0.40***	0.42***
	(4.34)	(4.49)	(4.87)
β^{H-BEAR}	–0.55***	–0.46***	–0.41**
	(–4.25)	(–3.52)	(–2.48)
Return [t]	0.10***	0.10***	0.11***
	(6.52)	(7.64)	(7.82)
Return [t–1]		0.03***	0.02**
		(3.05)	(2.38)
Return [t–2]			0.03***
			(3.00)
Adjusted R^2	0.09	0.14	0.18

Table A2.6: H-Bear factor exposure and hedge fund performance: Results from Lipper TASS database
The table reports the results regarding the predictive power of H-Bear factor exposure for future hedge fund returns using data from the Lipper TASS. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. Panel A presents the average returns and Fung-Hsieh alphas (in monthly percentages) of hedge fund portfolios sorted with respect to H-Bear beta. At the end of each month from December 1997 to November 2015, we sort hedge funds into quintiles according to their H-Bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) H-Bear betas. We hold these quintile portfolios for one month and present the average equal-weighted returns (from January 1998 to December 2015) and alphas for each quintile and for the Q5–Q1 portfolio. Panel B presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund excess returns in month $t+1$ on H-Bear beta (β^{H-BEAR}) and other control variables measured at the end of month t. The control variables include different fund characteristics, manager skill measure, and other measures of risks. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Univariate portfolio sorts

	Q1	Q2	Q3	Q4	Q5	Q5–Q1
Equal-weighted returns (%)	0.81	0.58	0.44	0.42	0.40	–0.42***
	(4.08)	(3.67)	(2.30)	(1.88)	(1.16)	(–3.55)
FH alpha	0.48	0.27	0.14	0.09	–0.04	–0.53***
	(4.31)	(4.66)	(2.10)	(1.33)	(–0.40)	(–4.07)

Panel B: Fama-MacBeth regressions

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.54***	0.01	0.05	0.01	0.07	0.23
	(3.81)	(0.06)	(0.53)	(0.05)	(0.68)	(1.32)
β^{H-BEAR}	–0.50***	–0.25***	–0.20***	–0.27***	–0.22***	–0.21***
	(–4.43)	(–4.46)	(–3.33)	(–4.14)	(–2.80)	(–2.99)
Size		0.01	0.00	0.01	0.00	0.00
		(0.65)	(0.49)	(0.66)	(–0.20)	(–0.29)
Age		–0.09	–0.18	–0.10	0.03	–0.03
		(–0.46)	(–0.89)	(–0.50)	(0.19)	(–0.18)
Min Investment		0.70***	0.67***	0.69***	0.68***	0.62***
		(5.27)	(5.07)	(5.00)	(4.35)	(3.70)
Management Fee		2.73	3.59	3.40	3.21	3.21
		(0.85)	(1.25)	(1.11)	(1.14)	(1.44)
Incentive Fee		0.05	0.09	0.06	0.06	0.04
		(0.38)	(0.60)	(0.47)	(0.49)	(0.36)
Lock Up		–0.57	–0.87	0.11	0.46	–0.11
		(–0.20)	(–0.34)	(0.04)	(0.19)	(–0.05)
Redemption		1.08**	0.87**	1.12**	0.76**	0.65
		(2.31)	(2.06)	(2.38)	(2.04)	(1.61)
Leverage		0.03	0.03*	0.02	0.03	0.02
		(1.50)	(1.94)	(1.45)	(1.50)	(1.45)
Hurdle		–0.02	–0.02	0.01	–0.06	–0.01
		(–0.14)	(–0.16)	(0.09)	(–0.61)	(–0.11)

HWM		0.08*	0.07*	0.08*	0.09**	0.08**
		(1.77)	(1.76)	(1.77)	(1.97)	(2.00)
Past return (12M)		2.33***	2.47***	2.37***	2.40***	2.06***
		(8.08)	(11.03)	(8.15)	(9.98)	(5.53)
Ret VOL (24M)		2.75	1.27	2.81	1.87	1.54
		(1.05)	(0.78)	(1.08)	(0.72)	(0.85)
Ret SKEW (24M)		0.03	0.05**	0.02	0.04*	0.04**
		(0.99)	(2.30)	(0.83)	(1.78)	(2.18)
Ret KURT (24M)		–0.01	–0.01	–0.01	–0.01	–0.01*
		(–0.89)	(–1.55)	(–0.92)	(–0.91)	(–1.69)
β^{MKT}			0.18			0.47**
			(0.80)			(1.97)
$\beta^{\Delta VOL}$				–0.05		0.01
				(–0.37)		(0.03)
$\beta^{\Delta SKEW}$				0.43		0.48
				(0.35)		(0.41)
TailRisk					0.19	–0.03
					(0.92)	(–0.34)
β^{UNC}						0.02
						(0.81)
β^{RIX}						–0.02*
						(–1.66)
R2						–0.16
						(–1.46)
SDI						0.01
						(0.09)
Downside Return						0.07
						(1.10)
Adjusted R^2	0.02	0.14	0.20	0.16	0.16	0.25

Table A2.7: H-Bear factor exposure and hedge fund performance: Results from EurekaHedge database
The table reports the results regarding the predictive power of H-Bear factor exposure for future hedge fund returns using data from the EurekaHedge. H-Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. Panel A presents the average returns and Fung-Hsieh alphas (in monthly percentages) of hedge fund portfolios sorted with respect to H-Bear beta. At the end of each month from December 1997 to July 2016, we sort hedge funds into quintiles according to their H-Bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) H-Bear betas. We hold these quintile portfolios for one month and present the average equal-weighted returns (from January 1998 to August 2016) and alphas for each quintile and for the Q5–Q1 portfolio. Panel B presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund excess returns in month $t+1$ on H-Bear beta (β^{H-BEAR}) and other control variables measured at the end of month t. The control variables include different fund characteristics, manager skill measure, and other measures of risks. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

Panel A: Univariate portfolio sorts

	Q1	Q2	Q3	Q4	Q5	Q5–Q1
Equal-weighted returns (%)	1.27	0.74	0.58	0.51	0.39	–0.87***
	(4.77)	(4.75)	(3.77)	(2.73)	(1.16)	(–3.23)
FH alpha	0.98	0.44	0.27	0.16	0.00	–0.98***
	(3.89)	(4.06)	(3.25)	(1.84)	(0.02)	(–2.93)

Panel B: Fama-MacBeth regressions

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.71***	0.47***	0.44***	0.43***	0.42***	0.44**
	(4.63)	(2.90)	(2.84)	(2.86)	(2.93)	(2.26)
β^{H-BEAR}	–0.55***	–0.41***	–0.30***	–0.40***	–0.46***	–0.40***
	(–3.55)	(–3.38)	(–2.86)	(–3.26)	(–3.27)	(–2.89)
Size		–0.05**	–0.04**	–0.04**	–0.04**	–0.02*
		(–2.37)	(–2.36)	(–2.39)	(–2.33)	(–1.85)
Age		–0.06	–0.06	–0.06	–0.06	–0.06
		(–1.01)	(–0.93)	(–1.06)	(–1.10)	(–1.23)
Min Investment		1.16***	1.15***	1.13***	1.24***	1.09***
		(3.21)	(3.52)	(3.53)	(3.36)	(3.43)
Management Fee		3.94	3.39	2.98	2.80	0.24
		(1.31)	(1.43)	(1.04)	(1.04)	(0.11)
Incentive Fee		–0.36	–0.25	–0.30	–0.44	–0.50*
		(–1.10)	(–0.97)	(–0.98)	(–1.36)	(–1.94)
Lock Up		0.42	0.25	0.34	0.41	–0.10
		(0.84)	(0.54)	(0.67)	(0.93)	(–0.27)
Redemption		0.00	0.01	0.00	0.01	0.00
		(0.18)	(0.31)	(0.15)	(0.41)	(0.22)
Leverage		0.06*	0.06*	0.05*	0.02	0.00
		(1.78)	(1.87)	(1.82)	(0.64)	(0.13)
Hurdle		–0.08	–0.10	–0.07	–0.05	–0.07
		(–1.03)	(–1.36)	(–0.87)	(–0.75)	(–1.01)

HWM		–0.02	–0.03	0.00	0.02	0.06
		(–0.37)	(–0.56)	(0.05)	(0.49)	(1.57)
Past return (12M)		1.24***	1.43***	1.22***	1.22***	0.81***
		(4.31)	(6.52)	(4.21)	(4.66)	(2.66)
Ret VOL (24M)		5.78**	6.90***	5.92**	7.31***	8.39***
		(2.28)	(3.44)	(2.27)	(3.56)	(4.48)
Ret SKEW (24M)		0.05	0.05	0.05	0.05	0.07
		(1.08)	(1.17)	(1.22)	(1.11)	(1.39)
Ret KURT (24M)		0.00	0.00	0.00	0.00	–0.01
		(0.12)	(–0.57)	(–0.08)	(–0.19)	(–1.26)
β^{MKT}			–0.01			0.27
			(–0.06)			(1.26)
$\beta^{\Delta VOL}$				–0.16		–0.01
				(–0.89)		(–0.11)
$\beta^{\Delta SKEW}$				1.07		1.10
				(0.54)		(0.54)
TailRisk					–0.09	–0.16
					(–0.67)	(–1.51)
β^{UNC}						0.02
						(0.99)
β^{RIX}						0.00
						(0.19)
R2						–0.10
						(–0.59)
SDI						–0.22***
						(–2.79)
Downside Return						0.08**
						(2.06)
Adjusted R^2	0.03	0.15	0.20	0.18	0.18	0.27

Appendix B

Appendix to Chapter 3

B1. Definition of variables for Chapter 3

B1.1. Firm- and stock-related characteristics

- $\boldsymbol{PRisk}$ (firm-level political risk): is measured as the proportion of the conversation in quarterly conference calls devoted to risks related to political topics. For details, see HHLT (2019). $PRisk$ for each firm in each month is based on the available political risk of the firm extracted from the most recent conference call. $PRisk$ is winsorized each month at (0, 95) and is normalized to have unit standard deviation.
- $\boldsymbol{PSentiment}$ (firm-level political sentiment): is measured by counting political bigrams conditioning on the proximity to words representing positive or negative sentiment based on the Loughran and McDonald (2011) sentiment dictionary. For details, see HHLT (2019). $PSentiment$ for each firm in each month is based on the available political sentiment of the firm extracted from the most recent conference call. $PSentiment$ is winsorized each month at (0.5, 99.5) and is normalized to have unit standard deviation.
- **EPU beta**: is estimated from a regression of monthly stock excess returns on the innovations of the economic policy uncertainty index controlling for the market excess returns over the past 60 months with a requirement of at least 36 months of non-missing stock returns.
- **Size:** is the natural logarithm of the market capitalization, which is the product of stock price and number of shares outstanding at the end of the month.
- **BM** (Book-to-market ratio)**:** is the ratio of a firm's book value of equity to its market value of equity where the market value of equity is the market capitalization at the end of the fiscal year. The book value of equity is total stockholders' equity (Compustat item "seq"), plus deferred taxes (Compustat item "txditc" or the sum of items "txdb" and "itcb" if "txditc" is missing), minus preferred stock (Compustat item "pstkrv", or "pstkl", or "pstk" in that order of availability).
- **IdioVol** (Idiosyncratic volatility)**:** is the standard deviation of the residuals, $\varepsilon_{i,\tau}$, from the regression of daily excess stock returns on daily Fama and French (1993) three factors: $r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta_{i,t}^{M} \times \left(r_{M.\tau} - r_{f,\tau}\right) + \beta_{i,t}^{S} \times SMB_{\tau} + \beta_{i,t}^{H} \times HML_{\tau} + \varepsilon_{i,\tau}$, over the past one month with a requirement of at least 15 non-missing daily stock returns.
- **Reversal:** is the cumulative stock return over the past one month.
- **Momentum:** is the cumulative stock return over the period from month $t-12$ to month $t-1$.

- **Illiquidity** (Amihud's (2002) stock illiquidity)**:** is computed as the average of the daily ratio of absolute return to dollar volume within the past one month (multiplied by 10^8). We require at least 15 daily observations.
- **Inst** (Institutional ownership): is the percentage of shares owned by institutional investors divided by the number of shares outstanding. Data are from Thomson Reuters Institutional (13f) Holdings.
- **Leverage:** is the ratio of total liabilities (Compustat item "lt") to total assets (Compustat item "at").
- **Profitability**: is the ratio of revenues (Compustat item "revt") minus costs of goods sold (Compustat item "cogs") to total assts (Compustat item "at")**.**

B1.2. Option-related characteristics

- **Volatility Deviation**: is the log difference between the realized volatility, calculated as the annualized standard deviation of daily stock returns over the past 12 months, and the at-the-money implied volatility. At-the-money implied volatility is defined as the average implied volatility of a call and a put option with absolute value of delta equal to 0.50 and 30 days to maturity. Data are from the Volatility Surface file.
- **VTS** (Volatility Term Structure): is the difference between the at-the-money implied volatility for options expiring in 91 days and that for options expiring in 30 days. At-the-money implied volatility for each horizon is defined as the average implied volatility of a call and a put option with absolute value of delta equal to 0.50. Data are from the Volatility Surface file.
- **RNS, RNK** (Risk-Neutral Skewness/Kurtosis): are the higher-order risk-neutral moments estimated as in Bakshi, Kapadia and Madan (2003) using options with 30 days to maturity and absolute delta lower or equal to 0.50. We interpolate the implied volatility smile using a cubic smoothing spline for the moneyness levels that range within the available data and extrapolate using the respective boundary values for moneyness levels outside the available data. The integrals of the formulas are estimated using the trapezoidal approximation. Data are from the Volatility Surface file.
- **VOV** (Volatility-of-Volatility): is the standard deviation of the percentage changes in at-the-money implied volatility within the month. At-the-money implied volatility is defined as the average implied volatility of a call and a put option with absolute value of delta equal to 0.50 and 30 days to maturity. We require at least 15 daily observations. Data are from the Volatility Surface file.
- **Volatility Spread**: is the difference between the implied volatility of a call option with delta equal to 0.50 and 30 days to maturity and that of a put option with delta equal to −0.50 and 30 days to maturity. Data are from the Volatility Surface file.
- **Option illiquidity**: is the ratio of the difference between the option ask and bid quotes to the midpoint of option bid and ask quotes.

B1.3. Other conditioning variables

- **Default probability:** We employ Bharath and Shumway's (2008) version of the Merton distance to default model to get estimates of default probability. Each month, a firm's default probability, $DP_{i,t}$, is calculated as follows:

$$DP_{i,t} = N\left(-\frac{\ln\left(\frac{V}{D}\right) + (r_{t-1} - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}\right)$$

where $N(.)$ is the cumulative normal distribution, V is the total value of the firm's assets, which equals the firm's market value of equity (ME) plus the face value of debt (D) in month t, T is the firm's debt maturity assumed equal to one year, r_{t-1} represents the expected return on the firm's total assets and is estimated as the annualized stock return from the past 12 months, and σ_V is the volatility of the firm's total assets. Specifically, σ_V is computed as the weighted average of the volatilities of the firm's equity and debt:

$$\sigma_V = \left(\frac{ME}{ME + D}\right)\sigma_E + \left(\frac{D}{ME + D}\right)\sigma_D$$

where σ_E is the volatility of the firm's equity estimated using monthly equity returns over the past 36 months, and σ_D is the volatility of the firm's debt estimated as: $\sigma_D = 0.05 + 0.25\sigma_E$. The face value of debt (D) equals current liabilities (Compustat item "dlcq") plus half the long-term debt (Compustat item "dlttq").

- **Analyst Coverage**: is the number of analysts following the firm. If the value is missing, it is set equal to zero. Data are obtained from IBES.
- **Analyst DISP**: is the dispersion in analysts' forecasts, computed as the standard deviation of analysts' earnings forecasts for the next fiscal year, scaled by the absolute value of the average earnings forecast. Data are obtained from IBES.
- **CVOL** (Cash flow volatility) is the standard deviation of quarterly operating cash flows (Compustat item "niq" plus Compustat item "dpq") scaled by total assets (Compustat item "atq") over the past five years.
- **Option demand**: is the ratio of the option open interest at the end of the month divided by the stock trading volume over the month.
- $\boldsymbol{lnLobby}$: is the natural logarithm of one plus a firm's lobbying expenses over the past four quarters.
- $\boldsymbol{lnDonate}$: is the natural logarithm of one plus a firm's campaign donations over the past four quarters.
- $\boldsymbol{Partisan}$: is a dummy variable that takes the value of one if the absolute difference between donations to Democratic and Republican political campaigns scaled by the total donation is above the median across firms in the month.

B2. Additional results for Chapter 3

Table B2.1: Panel regressions

This table presents the panel regression results for the effect of firm-level political risk on delta-hedged option returns. The dependent variable is the delta-hedged call or put option return in month $t+1$ (in percentage terms). The main independent variable is the standardized firm-level political risk ($PRisk$) at the end of month t based on the most recent conference call. Control variables include political sentiment, EPU beta, log of market cap, book-to-market ratio, idiosyncratic volatility, reversal, momentum, stock illiquidity, institutional ownership, leverage, and gross profitability. The industry fixed effects are defined by 2-digit SIC codes. Our sample spans the period from January 2003 to June 2019. Robust t-statistics, clustered at the firm level, are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns				Delta-hedged put option returns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PRisk$	−0.17***	−0.17***	−0.13***	−0.07***	−0.13***	−0.15***	−0.11***	−0.06***
	(−5.88)	(−7.45)	(−5.54)	(−2.87)	(−5.74)	(−7.47)	(−5.27)	(−3.01)
$PSentiment$		−0.04**	−0.01	−0.01		−0.03**	0.00	0.00
		(−2.27)	(−0.52)	(−0.34)		(−2.14)	(−0.39)	(−0.02)
EPU beta		−0.03	−0.01	−0.04		−0.06***	−0.03*	−0.05**
		(−1.37)	(−0.56)	(−1.32)		(−2.99)	(−1.91)	(−2.29)
Size		0.22***	0.22***	0.22***		0.21***	0.21***	0.24***
		(18.84)	(18.69)	(6.40)		(20.07)	(20.63)	(8.65)
BM		0.23***	0.06	−0.17***		0.20***	0.09***	−0.12***
		(4.51)	(1.19)	(−2.90)		(5.72)	(2.74)	(−3.00)
IdioVol		−1.88***	−1.79***	−1.41***		−1.58***	−1.53***	−1.16***
		(−19.73)	(−18.87)	(−14.38)		(−22.42)	(−22.13)	(−15.89)
Reversal		0.98***	1.03***	1.10***		0.12	0.15	0.15
		(7.74)	(8.18)	(8.64)		(1.20)	(1.52)	(1.47)
Momentum		0.12***	0.11***	0.16***		0.15***	0.14***	0.15***
		(4.63)	(4.34)	(5.61)		(7.12)	(6.91)	(7.00)
Illiquidity		−0.06*	−0.04	0.01		−0.03	−0.02	0.04*
		(−1.84)	(−1.59)	(0.28)		(−0.69)	(−0.41)	(1.85)
Inst		0.51***	0.54***	0.38***		0.50***	0.53***	0.15**
		(6.66)	(7.39)	(4.24)		(7.70)	(8.56)	(2.04)
Leverage		0.16**	0.01	−0.25**		0.14**	0.10*	−0.16
		(2.32)	(0.19)	(−2.00)		(2.54)	(1.83)	(−1.58)
Profitability		0.53***	0.66***	0.31**		0.36***	0.49***	0.29***
		(7.31)	(8.72)	(2.26)		(6.22)	(7.87)	(2.84)
Intercept	−3.86***	−7.15***	−6.94***	−6.85***	−3.05***	−6.27***	−7.51***	−6.27***
	(−15.85)	(−22.31)	(−23.44)	(−11.85)	(−16.26)	(−23.25)	(−29.86)	(−13.87)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	Yes	No
Firm FE	No	No	No	Yes	No	No	No	Yes
Cluster by firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113,288	98,230	98,230	98,230	113,288	98,230	98,230	98,230
R^2	0.15	0.18	0.19	0.18	0.21	0.25	0.26	0.24

Table B2.2: Firm-level political risk and IV–HV

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of IV–HV in month t on firm-level political risk ($PRisk$) and control variables measured at the end of month t. IV–HV is the difference between the implied volatility of the ATM call (or put) option at the end of month t and the historical volatility of the underlying stock return in month t. The main independent variable is the standardized $PRisk$. Control variables include political sentiment, EPU beta, log of market cap, book-to-market ratio, idiosyncratic volatility, return reversal, momentum, stock illiquidity, institutional ownership, leverage, and gross profitability. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	IV–HV	
	Calls	Puts
$PRisk$	0.006***	0.007***
	(8.41)	(8.52)
$PSentiment$	0.004***	0.004***
	(6.56)	(6.33)
EPU beta	–0.006**	–0.008***
	(–2.37)	(–2.68)
Size	–0.047***	–0.046***
	(–32.05)	(–34.30)
BM	–0.019***	–0.018***
	(–5.76)	(–5.15)
IdioVol	–0.692***	–0.663***
	(–65.14)	(–68.55)
Reversal	–0.161***	–0.126***
	(–18.79)	(–16.49)
Momentum	–0.008**	–0.010***
	(–2.37)	(–2.98)
Illiquidity	0.005***	0.004***
	(7.38)	(6.63)
Inst	–0.074***	–0.084***
	(–16.30)	(–20.70)
Leverage	–0.034***	–0.031***
	(–8.57)	(–7.17)
Profitability	–0.034***	–0.036***
	(–8.99)	(–10.05)
Intercept	1.002***	0.98***
	(36.56)	(41.18)
Adjusted R^2	0.39	0.37

Table B2.3: Firm-level political risk and option trading volume

This table reports the results from Fama and MacBeth (1973) cross-sectional regressions of an alternative measure of option demand pressure (option trading volume) on $PRisk$ and other control variables. Option trading volume within a month is scaled by stock trading volume in that month and is grouped into different categories: (1) total calls, (2) OTM calls, (3) ITM calls, (4) total puts, (5) OTM puts, and (6) ITM puts. We report the coefficients on $PRisk$; the coefficients on control variables are suppressed for the sake of brevity. Our sample spans the period from January 2003 to June 2019. Newey and West (1987) t-statistics with a lag length equal to four are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Total Calls	OTM Calls	ITM Calls	Total Puts	OTM Puts	ITM Puts
$PRisk$	0.40***	0.29***	0.11***	0.35***	0.28***	0.07***
	(3.99)	(4.20)	(2.68)	(5.07)	(5.67)	(2.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.14	0.12	0.16	0.10	0.11	0.12

Table B2.4: Response to earnings calls controlling for firm profitability and past stock return
This table reports the average monthly delta-hedged call and put option returns (in percentage terms) around unexpected increases and decreases in firm-level political risk. The surprise component for each firm's political risk is captured using an AR1 regression augmented with the contemporaneous EPU value, the lagged monthly stock return, and the concurrent value of firm's gross profitability We define unexpected increases (decreases) in firm-level political risk as the earnings calls that correspond to the top (bottom) tercile of this surprise component across the whole sample. We report the average delta-hedged option returns in the two months before and the two months after the earnings call month. Our sample spans the period from January 2003 to June 2019. t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Delta-hedged call option returns			Delta-hedged put option returns		
Political risk surprise	Increase	Decrease	Difference	Increase	Decrease	Difference
Pre-event return	−0.93	−0.98	0.05	−0.64	−0.75	0.11
Post-event return	−1.05	−0.94	−0.11	−0.81	−0.69	−0.12
Difference	−0.12*	0.04	−0.16*	−0.17***	0.06	−0.23***
	(−1.71)	(0.65)	(−1.67)	(−2.91)	(0.95)	(−2.71)

Appendix C

Appendix to Chapter 4

C1. Definition of variables for Chapter 4

C1.1. Fund-level variables

- $\boldsymbol{\beta_{Fund}^{Climate}}$ (fund-level climate beta): is the coefficient $\beta_{Fund_{i,t}}^{Climate}$ obtained from the regression of fund i's excess returns, on innovations in climate change news index with control for market, size, value, and momentum factors: $r_{Fund_{i,t}} = \alpha_{i,t} + \beta_{Fund_{i,t}}^{Climate} \times CH\_Climate_{\ t} + \boldsymbol{\beta'_{i,t}} \times \boldsymbol{F_t} + \varepsilon_{i,t}$, over a 24-month rolling window period with a requirement of at least 18 months of non-missing fund returns.
- **TNA**: is the fund's total net asset computed as the sum of TNAs of its share classes.
- **Flow**: is the fund flow computed as follows: $Flow_{i,t} = [TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t})] / \ TNA_{i,t-1}$, where $TNA_{i,t}$ refers to the total net asset of fund i in month t, and $r_{i,t}$ refers to fund i's total return in the same month.
- **Expense ratio**: is the fund's annualized expense ratio as reported in the CRSP mutual fund database.
- **Turnover**: is the fund's turnover ratio as reported in the CRSP mutual fund database.
- **Fund Age**: is the number of operational months since inception.
- **Tenure**: is number of months since the current portfolio manager took control.
- **Tracking Error**: is the standard deviation of the differences between monthly fund returns and its benchmark index returns over the most recent 24 months.
- **R-Squared**: is calculated following Amihud and Goyenko (2013) as R-squared from Carhart (1997) four-factor regression using monthly returns over the most recent 24 months.
- **Past Alpha**: is the risk-adjusted excess fund return from Carhart (1997) four-factor regression using monthly returns over the most recent 24 months.
- $\boldsymbol{Climate\_Score}$: is the fund-level score of climate beta stock holding and is calculated as: $Climate\_Score_{i,t} = \sum_j w_{j,i,t} \times \beta_{Stock_{j,t}}^{Climate}$, where $Climate\_Score_{i,t}$ is fund i's score of climate beta stock holdings in month t, $w_{j,i,t}$ is the investment weight of stock j in fund i in month t based on the most recent holding report, and $\beta_{Stock_{j,t}}^{Climate}$ is climate beta of stock j in month t.

C1.2. Stock-level variables

- $\boldsymbol{\beta^{Climate}_{Stock}}$ (stock-level climate beta): is the coefficient $\beta^{Climate}_{Stock_{j,t}}$ obtained from the regression of stock j's excess returns, on innovations in the CH negative sentiment climate change news index with control for market, size, value, and momentum factors: $r_{Stock_{j,t}} = \alpha_{j,t} + \beta^{Climate}_{Stock_{j,t}} \times CH_{Climate_t} + \boldsymbol{\beta'_{j,t}} \times \boldsymbol{F_t} + \varepsilon_{i,t}$, over a 24-month rolling window period with a requirement of at least 18 months of non-missing stock returns.
- **Size**: is the market capitalization, which is the product of price and number of shares outstanding at the end of the month
- **BM** (Book-to-market ratio) (Fama and French, 1992): is the ratio of a firm's book value of equity to its market value of equity where the market value of equity is the market capitalization at the end of the fiscal year. The book value of equity is total stockholders' equity (Compustat item "seq"), plus deferred taxes (Compustat item "txditc" or the sum of items "txdb" and "itcb" if "txditc" is missing), minus preferred stock (Compustat item "pstkrv", or "pstkl", or "pstk" in that order of availability).
- **Market beta**: is the coefficient on market excess returns from the regression of stock excess returns on market excess returns over a 60-month rolling window period. We require at least 36 months of non-missing stock returns.
- **Mom** (Momentum) (Jegadeesh and Titman, 1993): is the cumulative stock return over the period from $t - 12$ months to $t - 1$ month.
- **Rev** (Short-term reversal) (Jegadeesh, 1990): is the cumulative stock return over the past one month.
- **Leverage**: is the ratio of total liabilities (Compustat item "lt") to total assets (Compustat item "at").
- **R&D**: is the ratio of research and development expenses (Compustat item "xrd") to total assets (Compustat item "at").
- **Inst Own** (Institutional ownership): is the percentage of share owned by institutional investors divided by number of shares outstanding. Data are from Thomson Reuters Institutional (13f) Holdings.
- **Climate exposure, Climate risk, and Climate Sentiment**: are respectively the text-based measures of firm-level climate change exposure, risk, and sentiment extracted from conference call conversations and based on the most recent conference call available at the end of month t. For details, see Sautner et al. (2020).
- **E-Score**: is an overall environmental score at firm-level from KLD database and is calculated as subtraction of the total scores in the negative environmental subcategories from the total scores in positive environmental subcategories. Monthly scores are based on the last annual scores.
- **ΔE-Score**: is the difference between current year E-Score and last year E-Score.

C2. Additional results for Chapter 4

Table C2.1: Fund-level climate beta and mutual fund performance: Sensitivity tests

The table reports results from a series of sensitivity tests with respect to the average gross returns and alphas of mutual fund portfolios sorted by fund-level climate beta. We sort funds into quintiles based on their climate betas at the end of each month, hold these quintile portfolios for one month, and present the average returns and alphas for each quintile as well as the Q5–Q1 portfolio. We present results for both equal-weighted and value-weighted portfolios. In Specification (1), we estimate climate beta by further adding liquidity factor as control variable in Equation (1). In Specification (2), we estimate climate beta by further adding investment and profitability factors as control variables in Equation (1). In Specification (3), instead of tracking returns from the month immediately following portfolio formation, we skip one month. In Specification (4), we use rolling window of 36 months instead of 24 months to estimate climate beta. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	(1) Add Liquidity factor in Equation (4.1)		(2) Add profitability and investment factors in Equation (4.1)		(3) Skip one month		(4) Use 36 month rolling window	
	EW	VW	EW	VW	EW	VW	EW	VW
Q1	1.10	1.16	1.11	1.18	1.03	1.07	0.93	1.03
	(3.29)	(3.61)	(3.35)	(3.74)	(3.05)	(3.30)	(2.84)	(3.27)
Q2	1.14	1.15	1.14	1.16	1.06	1.09	0.97	1.01
	(3.54)	(3.74)	(3.61)	(3.91)	(3.37)	(3.66)	(3.23)	(3.50)
Q3	1.17	1.18	1.17	1.18	1.11	1.11	0.98	1.00
	(3.63)	(3.82)	(3.66)	(3.85)	(3.43)	(3.58)	(3.15)	(3.37)
Q4	1.20	1.19	1.20	1.22	1.16	1.17	0.99	1.01
	(3.63)	(3.81)	(3.59)	(3.90)	(3.53)	(3.74)	(3.15)	(3.35)
Q5	1.28	1.34	1.26	1.33	1.25	1.30	1.02	1.11
	(3.69)	(4.10)	(3.57)	(3.99)	(3.68)	(4.12)	(3.18)	(3.74)
Q5–Q1	0.19***	0.18*	0.15***	0.15*	0.22***	0.23*	0.09*	0.08
	(2.85)	(1.76)	(2.68)	(1.80)	(3.28)	(2.11)	(1.77)	(0.85)
Q5–Q1 FFC α	0.17**	0.18**	0.12**	0.15**	0.21***	0.25***	0.10*	0.13
	(2.54)	(2.20)	(2.31)	(2.07)	(3.30)	(2.69)	(1.93)	(1.62)
Q5–Q1 FFCPS α	0.19***	0.22**	0.12**	0.16**	0.22***	0.27***	0.10*	0.15
	(2.84)	(2.64)	(2.13)	(2.19)	(3.39)	(2.88)	(1.72)	(1.58)

Table C2.2: Long-term predictive power of fund-level climate beta for mutual fund performance
The table reports the time-series average of kth-month ahead excess returns for each of the fund quintiles formed each month on the basis of their climate betas as well as the average kth-month ahead return and alpha differences between the high and low climate beta quintiles (Q5–Q1). All portfolios are equal-weighted. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	t+2	t+3	t+4	t+5	t+6
Q1	1.03	1.10	1.02	0.99	1.01
	(3.05)	(3.12)	(3.08)	(3.03)	(3.03)
Q2	1.06	1.13	1.05	1.02	1.03
	(3.37)	(3.42)	(3.42)	(3.33)	(3.32)
Q3	1.11	1.17	1.07	1.04	1.04
	(3.43)	(3.45)	(3.38)	(3.32)	(3.31)
Q4	1.16	1.23	1.12	1.07	1.06
	(3.53)	(3.58)	(3.52)	(3.40)	(3.31)
Q5	1.25	1.31	1.19	1.16	1.12
	(3.68)	(3.70)	(3.65)	(3.57)	(3.45)
Q5–Q1	0.22***	0.21***	0.17**	0.17**	0.11*
	(3.28)	(3.42)	(2.51)	(2.51)	(1.69)
Q5–Q1 FFC α	0.21***	0.21***	0.18***	0.16**	0.10
	(3.30)	(3.66)	(2.81)	(2.44)	(1.57)
Q5–Q1 FFCPS α	0.22***	0.21***	0.18***	0.13**	0.07
	(3.39)	(3.64)	(2.87)	(1.99)	(1.15)

Table C2.3: Fund-level climate beta and mutual fund performance: Results from changes in Google SVI climate change index

The table reports results of portfolio sorts based on fund-level climate beta with respect to changes in SVIs on search topic “climate change” constructed by Google Trends. In each month and for each mutual fund, climate beta is estimated from a regression of mutual fund excess returns on changes in Google SVI climate change index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from Jan 2006 to Nov 2019 we sort funds into quintiles according to their climate betas. We report the next month’s average of gross returns (both equal-weight and value-weight) within each quintile and the average return difference between the top and bottom quintiles (the time series of returns for each quintile from Feb 2006 to Dec 2019). For risk-adjusted returns, we use the one-factor model of CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the four-factor model augmented with Pastor and Stambaugh (2003) liquidity factor. Newey and West (1987) t-statistics are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	Equal-Weight (%)					Value-Weight (%)				
	Ret	CAPM α	FF α	FFC α	FFCPS α	Ret	CAPM α	FF α	FFC α	FFCPS α
Q1	0.67	–0.18	–0.15	–0.15	–0.15	0.73	–0.10	–0.10	–0.09	–0.09
	(1.58)	(–3.12)	(–3.32)	(–3.33)	(–3.38)	(2.04)	(–1.45)	(–1.53)	(–1.52)	(–1.56)
Q2	0.73	–0.09	–0.06	–0.06	–0.06	0.70	–0.12	–0.13	–0.13	–0.13
	(1.82)	(–1.71)	(–1.24)	(–1.21)	(–1.23)	(1.95)	(–2.08)	(–2.37)	(–2.35)	(–2.38)
Q3	0.77	–0.07	–0.05	–0.04	–0.04	0.78	–0.05	–0.05	–0.05	–0.05
	(1.89)	(–1.40)	(–1.19)	(–1.19)	(–1.12)	(2.22)	(–0.96)	(–1.20)	(–1.18)	(–1.09)
Q4	0.81	–0.04	–0.03	–0.03	–0.03	0.83	–0.01	–0.03	–0.03	–0.03
	(1.93)	(–0.77)	(–0.60)	(–0.58)	(–0.56)	(2.26)	(–0.16)	(–0.51)	(–0.49)	(–0.55)
Q5	0.88	0.00	0.02	0.02	0.01	0.91	0.04	0.02	0.03	0.02
	(2.03)	(0.05)	(0.26)	(0.27)	(0.18)	(2.36)	(0.50)	(0.32)	(0.34)	(0.26)
Q5–Q1	0.21***	0.18***	0.17**	0.17**	0.16**	0.18**	0.14*	0.12	0.12	0.11
	(3.16)	(2.71)	(2.46)	(2.42)	(2.35)	(2.28)	(1.79)	(1.58)	(1.55)	(1.49)

Table C2.4: Stock-level climate beta and expected stock return: Cross-sectional regressions

The table reports results from Fama-MacBeth (1973) cross-sectional regressions of stock excess returns in month $t+1$ (in percentages) on stock-level climate betas and other control variables measured at the end of month t. Stock-level climate beta ($\beta_{Stock}^{Climate}$) is estimated from a regression of stock excess returns on innovations in the CH negative sentiment climate change news index controlling for market, size, value, and momentum factors over the past 24 months with a requirement of at least 18 months of non-missing fund returns. The control variables include E-Score, ΔE-Score, Climate exposure, Climate risk, Climate sentiment, market beta, firm size, book-to-market ratio, momentum, reversal, institutional ownership, leverage, and R&D expenses over total assets. All independent variables are winsorized each month at the 0.5% level. A detailed definition of these variables is provided in Appendix C1. The sample period spans from Jul 2010 to Jun 2018. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)
$\beta_{Stock}^{Climate}$	0.35**	0.35**	0.35**	0.35**
	(2.53)	(2.39)	(2.35)	(2.35)
Market beta	–0.24	–0.26	–0.26	–0.25
	(–1.18)	(–1.22)	(–1.39)	(–1.32)
Log(Size)	–0.08	–0.06	–0.04	–0.04
	(–1.43)	(–1.13)	(–0.91)	(–0.98)
BM	–0.15	–0.15	–0.06	–0.06
	(–0.88)	(–0.89)	(–0.34)	(–0.38)
Mom	0.18	0.17	0.23	0.22
	(0.60)	(0.58)	(0.99)	(0.97)
Rev	–0.40	–0.35	–1.07*	–1.05*
	(–0.57)	(–0.49)	(–1.90)	(–1.88)
Inst Own	0.39**	0.34**	0.56***	0.59***
	(2.21)	(2.09)	(2.59)	(2.69)
Leverage	–0.27	–0.25	–0.32	–0.35
	(–0.83)	(–0.73)	(–0.92)	(–1.01)
R&D	0.00	0.03	–0.01**	–0.01**
	(–0.55)	(1.33)	(–2.46)	(–2.45)
E-Score	0.10			
	(1.39)			
ΔE-Score		0.24		
		(0.85)		
Climate exposure			–0.11*	
			(–1.70)	
Climate risk				–0.01
				(–0.41)
Climate sentiment				–0.03
				(–1.16)
Constant	2.46***	2.23**	1.78**	1.77**
	(2.58)	(2.41)	(2.43)	(2.43)
Adjusted R2	0.061	0.065	0.046	0.045

Table C2.5: Long-term predictive power of stock-level climate beta for expected stock returns

The table reports the time-series average of kth-month ahead excess returns for each of the stock quintiles formed each month on the basis of their stock-level climate betas as well as the average kth-month ahead return and alpha differences between the high and low climate beta stock quintiles (Q5–Q1). All portfolios are equal-weighted. Newey and West (1987) t-statistics with a lag length equal to three are reported in parentheses. *, **, and *** represent significance levels at 10%, 5%, and 1%.

	t+2	t+3	t+4	t+5	t+6
Q1	1.12	1.10	1.19	1.12	1.13
	(2.66)	(2.54)	(2.71)	(2.61)	(2.61)
Q2	1.35	1.25	1.34	1.28	1.18
	(3.75)	(3.48)	(3.49)	(3.64)	(3.38)
Q3	1.40	1.40	1.44	1.32	1.31
	(4.00)	(3.95)	(4.02)	(3.91)	(3.92)
Q4	1.45	1.38	1.50	1.39	1.42
	(4.16)	(4.02)	(4.08)	(4.07)	(4.15)
Q5	1.50	1.41	1.48	1.33	1.28
	(3.47)	(3.35)	(3.34)	(3.22)	(3.12)
Q5–Q1	0.38***	0.31***	0.28**	0.21*	0.15
	(3.49)	(2.96)	(2.34)	(1.71)	(1.38)
Q5–Q1 FFC α	0.26**	0.23**	0.22*	0.16	0.10
	(2.30)	(2.04)	(1.71)	(1.18)	(0.89)
Q5–Q1 FF6 α	0.25**	0.21*	0.20*	0.15	0.10
	(2.12)	(1.90)	(1.66)	(1.20)	(0.99)