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The Swedish Value Premium and Disasters: The Missing Piece of the Puzzle?

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ABSTRACT

This paper examines the value premium puzzle in Sweden for the period 2002 - 2016 and attempts to explain the puzzle by accounting for time-varying risk exposure with the inclusion of a proxy for financial disasters risk. The value premium is one of the most persistent financial anomalies and the reasons for its existence have been a hot topic for debate over the past years, with more recent research suggesting that it is a form of compensation for higher exposure to harsh economic downturns, or disasters. We elect to study this possibility empirically, through the conditional CAPM framework using the method presented by Petkova & Zhang. Firstly, we show that the value premium puzzle disappears around the time of the financial crisis and actually inverts post-crisis. We argue that this inversion is mainly due to the effects of financial restrictions which emerged during the crisis and the consequences to firms' capital structures. Secondly, and more importantly, we show that the inclusion of a disaster proxy in the conditional CAPM, the iTraxx credit default swap index, allows for the conclusion of disaster risk being priced into the value premium with our results going in the right direction in capturing the HML portfolio returns and explaining the movements in the portfolio beta.

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1. Introduction

Value stocks, or firms with high book to market values, comparatively outperform growth stocks, or firms with low book to market values, (Rosenberg et. al., 1985; Fama & French, 1992) despite similar betas. This phenomenon, the value premium, has been one of the most persistent anomalies in finance and was made famous by Fama & French through the HML factor incorporated in their three-factor model (Fama & French, 1992; Fama & French, 1993). We find that in the Swedish sample from 2002 to 2016, the monthly HML portfolio return is 0.41% ($t = 1.59$) and the monthly abnormal return, the CAPM alpha, is 0.22% ($t = 3.08$).

The reason for the premiums existence remain subject to dispute among researchers, where some believe that a viable explanation is time-varying risk exposure (Petkova & Zhang, 2005), the idea that risk of value-minus-growth strategies is high in bad times and low in good times, while others argue from more behavioral standpoints (Lakonishok et. al., 1994; DeBondt & Thaler, 1987). We adopt the first time-varying risk viewpoint, and add a proxy for disaster risk, the iTraxx index, based on more recent research which suggests that incorporating the probability of financial disasters goes in the right direction in explaining the risk premium, as value stocks are more exposed to the disaster risk than growth stocks (Bai et. al, 2019).

Our paper studies the value premium puzzle pre-, during, and post- the financial crisis of 2008, where we find that the HML CAPM alpha is large and significant pre-crisis ($\alpha = 0.95\%, t = 10.15$), insignificantly different from 0 during the crisis ($\alpha = 0.06\%, t = 1.70$), and in fact, negative post-crisis ($\alpha = -0.22\%, t = -2.21$). We attribute this variation in the premium to the changes in firms' capital structures during the subprime crisis (Bliss et. al., 2015) with the more leveraged firms becoming financially distressed and thus failing to hoard cash like their peers. This failure to internally finance, during the supply shock to the capital markets, has strong negative effects on the returns of the HML portfolio (Lee et. al., 2014) mainly due to the innate higher financial risk of value firms (Cao, 2015), which subsequently leads to a lower premium. Investors receive lower risk compensation with the previously higher financial leverage acting as a major driver of the premium (Cao, 2015). The investment irreversibility factor, as laid out in Zhang's fundamental model (Zhang, 2005), plays a role in the variation seen within portfolio returns during the subprime crisis but through different channels than previously suggested (Cao, 2015).

We then continue to present our main finding, which is the fact that accounting for disasters helps in explaining the value premium puzzle. Replicating Petkova and Zhang's framework (Petkova & Zhang, 2005), we find significant explanatory power when accounting for time-varying risks with the conditional market regressions being able to capture a lot of variability in the returns. This is seen both in the higher predicted market exposure (through the higher beta values during periods of financial distress) and in the significant and positive beta premium sensitivities produced in our tests. After adding the iTraxx variable, two results emerge. First, we find that the HML portfolio has a significant and positive beta premium sensitivity indicating a large time-varying risk exposure when accounting for the added disaster risk and second, that the inclusion of our credit default swap index, acting as a disaster proxy, improves both the variability captured in the conditional market regressions and in significantly explaining the movements within the HML portfolio betas ($\mathrm{t} = -2.20$). These results confirm the theoretical framework that Bai et. al. presented in their paper in a practical manner and indicate that disaster risk is, in fact, priced into the HML portfolio returns.

This paper is organized as follows: Section 2 presents the relevant previous literature and our contributions, Section 3 discusses the data and our empirical methodology, Section 4 shows our results and analysis, and Section 5 concludes the paper and discusses the implications of our findings.

2. Literature Review

2.1 Factor Models

When Kenneth French and Eugene Fama first quantified the HML factor and created their three-factor model (Fama & French, 1992; Fama & French, 1993) they started with the simple observation that two classes of stocks, small caps and stocks with high book-to-market values, tend to outperform the market as a whole. Since their paper in 1992, the pair have continued their studies with their three-factor model, as presented in their original paper, explaining over 90% of the diversified portfolio returns, with the CAPM average (within their sample) being closer to 70% (Fama & French, 1993). Traditional models, such as the Sharpe-Lintner CAPM, have often received criticism for failing to properly capture the variation in asset returns with Fama and French (Fama & French, 1993) pointing out that the average return of US common stocks show little relation to the beta of both the Sharpe-Lintner CAPM (Sharpe, 1964; Lintner, 1965) and the consumption CAPM (Breeden, 1979).

2.2 International Applications of Factor Models

The factor model approach that Fama and French established throughout their series of published papers have been applied to multiple geographical datasets, including United Kingdom (via University of Exeter), Germany (via The Technical University of Munich), Switzerland (via The University of St. Gallen) as well as Sweden (via The Stockholm School of Economics/Swedish House of Finance). Fama and French themselves contributed by performing multiple tests on international (non-US) markets in order to study what drives returns throughout different geographies (Fama & French, 1998; Fama & French, 2011). In their international studies, Fama and French conclude that the value premium is size dependent and decreases as firms get larger (Fama & French, 2011).

2.3 The Value Premium

Lu Zhang (Zhang, 2005) proposes that the costly reversibility, or at times even irreversibility, of capital investments, acts as a main factor for the premium's existence. He concludes that value firms are characterized by larger capital stocks than growth firms and that during periods of financial distress value firms are often forced to unwind their assets at large costs.

Viet Nga Cao also touches upon the reason regarding the premium's existence in her 2015 paper (Cao, 2015). Cao concludes that differences in financial leverage act as the main driver behind the existence of the premium although investment irreversibility does, as suggested by Zhang, play a role but through different channels than previously proposed. Her findings also indicate that operating leverage, in itself, does not notably influence the premium. The paper's conclusion draws from the fact that value firms often have larger financial risk and that in the absence of such differences in leverage there, instead, would exist a growth premium.

Petkova and Zhang argue that one needs to consider the differing risk exposure of value and growth firms and study their relative risk in order to properly understand the existence of the premium (Petkova & Zhang, 2005). Using the conditional CAPM and conditional market regressions, they find that value stocks possess larger time-varying risk exposure than growth stocks. This is especially captured via the positive beta premium sensitivities of value stocks that indicates higher risk during periods of financial distress. These results allow them to explain the outperformance of value stocks compared to growth stocks.

2.4 Disasters

In economics, disasters are defined as "infrequently occurring events that have substantial negative effects on the economy" (Rietz, 1988; Barro, 2006). Rietz coined the concept in his explanation of the equity premium puzzle laid out in Mehra and Prescott's 1985 paper (Mehra & Prescott, 1985). Rietz's original definition of a disaster is now considered extreme (Barro, 2006), and the contemporary definition is that a disaster is a rare event that has a substantial impact on the state of an economy in terms of changes within that economy's gross GDP and aggregate consumption (Wachter, 2013).

In a paper published in 2019 by Bai et. al. (Bai. et. al., 2019) a theoretical equilibrium model incorporating disasters is used to test if, under these conditions, the Breeden's consumption CAPM (Breeden, 1979) can explain the difference in returns between value and growth stocks. While the paper uses simulated models, it does shine light on how the returns of value stocks act as compensation for the risk that holders of those assets take on. The authors draw the conclusion that value stocks, or firms with high book-to-market values, have higher volatility and lower returns during disaster periods as shown by their simulated general equilibrium model rather than through real-world disasters.

The conclusion of disasters impacting consumption, and via that passage equity returns, had been suggested in a paper by Jessica Wachter. In her 2013 paper Wachter finds that aggregate consumption is often quite stable, and thus the equity premium as well (Wachter, 2013). However, the possibility of market turmoil, via the negative effects on aggregate consumption, increases the equity premium. Her discussion draws from earlier papers discussing the equity premium including Rietz 1988 paper (Rietz, 1988) in which it was proposed that the market return is at a higher level as a compensating factor for investor exposure towards the risk of rare disasters. Rietz's conclusion also draws from the fact that his model (similarly to Barro's disaster paper (Barro, 2006)) assumes that stock market returns equal the variability, and fundamentally the volatility, in dividends. Although firms often limit their distribution policies during periods of financial distress (Bliss et. al., 2015), other papers have disproven the one variable relationship (Keim & Stambaugh, 1986; Wachter, 2013). They show that the volatility of dividends alone does not provide sufficient explanatory power in explaining the volatility of returns, meaning that additional metrics, such as those presented in Petkova and Zhang's 2005 paper, are needed in explaining the variation of portfolio returns. In their 2005 paper Petkova and Zhang (Petkova & Zhang, 2005) incorporate the dividend yield as one component in conjunction with the term premium (the spread between 1 and 10-year treasury bond yields), the default spread (the yield premium between AAA and BAA-rated bonds) and the risk-free rate. The variables act in cohesion in order to model the expected market risk premium.

The pair motivate their selection with references to several papers, including Fama and French's 1988 paper (Fama & French, 1988) for the dividend yield, Fama and Schwert (Fama and Schwert, 1977) as well as Fama (Fama, 1981) for the inclusion of the risk-free (treasury yield) rate, Keim and Stambaugh (Keim et. al., 1986) for the default premium, and Campbell (Campbell, 1987) as well as Fama and French (Fama & French, 1989) for the term premium.

The world has experienced multiple instances of financial disasters, including the panic of 1907 and the Wall Street crash of 1929. More recent events include the Dot-Com Bubble of the 2000s and the Subprime crash of 2008-2009. While the severity of the disasters varies, the general consensus about the subprime crisis is that it was one of the worst financial disasters to have happened.

The value premium's variation during periods of financial distress is studied in a paper by Lee et. al. (Lee et. al., 2014). The authors find that value stocks actually underperform growth stocks, meaning that the premium inverts, during the subprime crisis. The inversion of the premium during the recession stands in contrast to the strong and positive premium that existed prior to the recession. The authors view their results as having implications on both the causes of the premium and the investment opportunity of it. The implications of the results presented in Lee et. al. are in agreement with the conclusion and results of the disaster study by Bai et. al. Both, although through different methods of study, conclude that value stocks are more exposed towards periods of financial distress, i.e. disaster events.

Several authors have performed disaster studies by attempting to quantify market turbulence and volatility in different metrics, similarly to how Bai et. al. (Bai et. al, 2019) and Wachter (Wachter, 2013) used consumption. Berkman et. al. report their creation of a crisis index after conducting studies on 447 instances of international crises (between 1918 - 2006) (Berkman et. al., 2011). They estimate that changes within their index, which they use as a proxy for the disaster probability, can predict the volatility in global stock market returns. They also find a correlation with the additional metrics such as earnings, price to earnings ratio, and dividend yield but, perhaps most notably, that industries that are sensitive towards crisis risk yield higher returns.

The implication for our paper, and fundamentally the entire disaster risk explanation, is whether the disaster risk exposure is actually priced into the returns of value stocks. Although Rietz paper (Rietz, 1988) received a lot of criticism (Barro, 2006), the theoretical framework laid out by Bai et. al. shines new light on the disaster risk explanation of the value premium (Bai et. al., 2019). Even though the literature contains suggestions of several risk drivers of the value premium through various passages (Cao, 2015; Zhang, 2005; Fama & French, 1992), there exists little literature examining the possibility of disaster risk exposure being priced into the value premium, as implied by the results laid out by Bai et. al. (Bai et. al., 2019).

3. Data and methodology

3.1 Data

In the study of the variation of the HML portfolios returns we retrieve the factor returns with monthly frequencies via the Swedish House of Finance's dataset for the Fama and French three-factor model. The dataset is comprehensive and includes all Swedish firms on the Stockholm Stock Exchange for our entire period. Firms that are delisted at any point in our period remain in the historical sample, which eliminates any survivor biases.

We use the same definitions for the conditioning variables as Petkova and Zhang, and adapt the variables to the Swedish market using the relevant metrics collected from several different sources including Bloomberg and Moody's.

We retrieve the 10 year and 1-year Swedish treasury yields via Bloomberg in order to calculate the term premium. For this calculation, we elect to use zero-coupon bonds (coupon stripped) in order to avoid the effects of mismatching coupon rates. The dividend yield of value-weighted index (SIXGX) composed of all shares listed on the Stockholm Exchange is also retrieved via Bloomberg. The yield is calculated, as in the original paper, on the dividends received in the last 12 months. The short-term risk-free rate data is retrieved via the Swedish House of Finance's database. The relevant (European) spreads between AAA and BAA3 bonds are retrieved via Moody's in order to calculate the default premium. As Petkova & Zhang did not explicitly specify which BAA rating they use, we made the decision to incorporate the "bottom" of the investment grade spectrum with BAA3 rated bonds. This provides a relevant metric in the default premium by capturing the entire range of investment grade credits.

To study if the disaster risk exposure suggested by Bai et. al. is priced into the value premium, we gather data on the iTraxx crossover index for the available period of 06/2004 - 12/2016. iTraxx is the collective name for several credit default swap indices covering a wide range of regions including Europe, Australia, and Asia. The main index was formed in 2004 following the merger of two different indices, including the iBoxx CDS created by iBoxx and the Trac-X index jointly created by JP Morgan and Morgan Stanley. The main index, the iTraxx Europe Index, is retrieved via Bloomberg and covers the 125 most liquid credit default swaps referencing European Investment Grade Credits with the rolling of the index constituents occurring every six months. In our collection of the iTraxx index data, we note that it was created in June 2004 and thus, in our tests, elect to focus the conditional market regressions over the period of the index's existence. There are several versions of the iTraxx index covering sector-specific and lower-grade credits, but our motivation for selecting the main iTraxx index for our study stems from the fact that it targets Europe, the geographical area most closely correlated with the Swedish market, and from the fact that it dates back the furthest. We motivate the usage of this variable and its ability in acting as a disaster proxy using the following arguments: A credit crunch is often one of the first things to occur during a disaster event, and many investors consider an inverting yield curve as a signal of weakening sentiment in the market. The implication is that credit market-related instruments can provide valuable insight into investors thoughts about the future which affects the prices of both equity and fixed income securities today. As credit default swaps allow investors to exchange their credit risk exposure with that of another investor, the pricing of such financial products is closely correlated to the overall credit risk within an economy.

Credit market characteristics are tightly linked to firm behavior which became especially evident during the financial crisis of 2007/2008. During the subprime crisis, many firms experienced liquidity problems due to the decreased credit supply. A study conducted by Bliss et. al. (Bliss et. al., 2015) concluded that firms during the subprime crisis maintained larger cash balance than they did previously. They also altered their payout policy, creating a substitute form of financing in response to the negative supply shocks to financing from the capital markets. This decrease in payout was most noticeable in firms with higher leverage but also in firms with more valuable growth options and lower cash balances. Following Cao's (Cao, 2015) argument about value stocks having higher financial risk, the sensitivity towards credit markets should play a role in firm behavior and asset returns as evident by Bliss. et. al. and Lee et. al. driving our hypothesis of a credit default swap index capturing the differing risk exposure of value and growth stocks.

3.2 Methodology

To begin our study, the existence of the value premium, and its variation across time, are examined in our selected market. If the premium exists in our sample of 2002-2016, we would expect to see positive returns for the long (value)/short (growth) HML portfolio as laid out by Fama & French.

In order to study the variation of the portfolio returns in our sample, the time-period is divided into sub-periods. We elect to use a division that is in accordance with the literature covering the crisis and other disaster studies, including the 2014 study by Lee et. al., in order to be consistent with the previous research. The total period is therefore split into three sub-periods defined as: pre-crisis (01/2002-04/2007), mid-crisis (04/2007-12/2008) and post-crisis (12/2008-12/2016).

In the examination of portfolio returns, we use the CAPM to study the model's explanatory ability over the returns and to examine if the value premium puzzle, or in other words, the CAPM's inability to capture the returns, exists. For these tests, different window sizes for rolling betas, namely 12, 24, and 36 months, are tested. We find that they all yield similar results (not reported) and elect to use the 24-month window as it is consistent with the literature including Petkova & Zhang's test on different windows for rolling beta (where they test both 24, 36 and 60 months and find no significant difference between them). These results, in conjunction with our shorter (~14 years) timespan compared to Petkova & Zhang's more substantial 74 years, motivate our selection of the shorter window size. The 24-month rolling window is both used in the study of the premium's variation (and the CAPM's ability to capture the returns) and in the sorting procedure Petkova & Zhang presented. We elect to also incorporate the same window size, for consistency, in our tests of the disaster variables' explanatory power over the movements in those betas.

Having studied the premiums variation, we move onto studying time-varying risk. We construct the dataset using monthly data, thereby replicating Petkova & Zhang's method. The dataset is merged together from the variables described in our data section.

We then continue to study the expected market risk premium. We model the expected risk premium both with and without the inclusion of our disaster variable in order to study the variable's explanatory power. As both the expected market risk premium and the conditional betas are unobservable metrics, we need to estimate them from the conditioning variables. In the calculations of the expected market risk premium, the realized market return is regressed on the conditioning variables known at time t using lagged values of those variables. This is modeled by the following equation:

$$r_{mt+1} = \delta_0 + \delta_1 DIV_t + \delta_2 DEF_t + \delta_3 TERM_t + \delta_4 TB_t + e_{mt+1} \tag{1}$$

Afterwards, we strip out the realized return and incorporate the results of the regression into the calculations of the estimated market risk premium:

$$\widehat{\gamma_t} = \widehat{\delta_0} + \widehat{\delta_1} DIV_t + \widehat{\delta_2} DEF_t + \widehat{\delta_3} TERM_t + \widehat{\delta_4} TB_t \tag{2}$$

The initial fit of the expected market risk premium is performed using Petkova and Zhang's suggested variables. Then, a modified fitting of the expected market risk premium is performed with the inclusion of the iTraxx index, making the equation:

$$r_{mt+1} = \delta_0 + \delta_1 DIV_t + \delta_2 DEF_t + \delta_3 TERM_t + \delta_4 TB_t + \delta_5 iTraxx_t + e_{mt+1} \quad (3)$$

With the fitted equation of the expected market risk premium being:

$$\widehat{\gamma_t} = \widehat{\delta_0} + \widehat{\delta_1} DIV_t + \widehat{\delta_2} DEF_t + \widehat{\delta_3} TERM_t + \widehat{\delta_4} TB_t + \widehat{\delta_5} iTraxx_t \quad (4)$$

Although studies have noted how the equity premium is at a higher level due to disaster risk exposure (Rietz, 1988; Barro, 2006) the concept of disasters affecting the entire risk premium has received criticism with other papers covering the topic stirring away from Rietz original explanation (Wachter, 2013). Bai. et. al. (Bai et. al., 2019) instead focus their study on the disaster exposure of a specific portfolio rather than the equity market premium as a whole. Although our hypothesis, based on the implications from Bai et. al., is that disaster risk exposure should capture the returns of the HML portfolio, it is not explicitly certain that the modified fitting of the expected market risk premium deviates from the fitted premium incorporating only the original metrics. The disaster variable is expected, as implied via the literature, to have a stronger impact in explaining the movements within the HML betas or in capturing the returns (and minimizing the alpha) when using conditional market regressions.

Having specified the expected market risk premium, we examine the conditional betas for value stocks. In our calculations of the conditional betas, we use the method presented in Petkova & Zhang. Conditional betas are defined as:

$$\beta_{it} = Cov_t[r_{it+1}, r_{mt+1}]/Var_t[r_{mt+1}] \quad (5)$$

Both the expected market risk premium and the betas are calculated using lagged values of the variables. Following Jagannathan and Wang (Jagannathan & Wang, 1996) and the method presented in Petkova and Zhang the equation becomes:

$$E[r_{it+1}] = \bar{\gamma}\bar{\beta}_i + Cov[\gamma_t, \beta_{it}] = \bar{\gamma}\bar{\beta}_i + Var[\gamma_t]\varphi_i \quad (6)$$

Where γ_t = Expected market risk premium, β_i = conditional betas and φ_i = beta premium sensitivity, defined as $\varphi_i = Cov[\beta_{it}, \gamma_t]/Var[\gamma_t]$. $\bar{\gamma} = E[\gamma_t]$ is the average market excess return and $\bar{\beta}_i = E[\beta_{it}]$ is the average beta.

The conditional betas are regressed on the expected market risk premium in order to examine the beta premium sensitivities. As the conditional CAPM uses beta premium sensitivity as a metric for the instability of an asset's or portfolio's beta over the business-cycle, the results of the regressions indicate whether or not value stocks are exposed to high risks during disaster periods - or in other words periods where the price of risk is high. If investors holding value stocks or an HML portfolio are exposed to a larger risk during downturns than they otherwise are, we would expect positive values of the beta premium sensitivities. The regressions are run using both the "traditional fitted" betas and the fitted betas that include our disaster proxy iTraxx. For the calculation of the fitted betas using the conditioning variables, we first perform the conditional market regressions using the previously defined variables:

$$r_{it+1} = \alpha_i + (b_{i0} + b_{i1}DIV_t + b_{i2}DEF_t + b_{i3}TERM_t + b_{i4}TB_t)r_{mt+1} + \varepsilon_{it+1} \qquad (7)$$

And then fit the conditional betas from those results:

$$\widehat{\beta_{it}} = \widehat{b_{i0}} + \widehat{b_{i1}}DIV_t + \widehat{b_{i2}}DEF_t + \widehat{b_{i3}}TERM_t + \widehat{b_{i4}}TB_t \qquad (8)$$

A second fitting is performed with the incorporation of the iTraxx index in the conditional market regressions:

$$r_{it+1} = \alpha_i + (b_{i0} + b_{i1}DIV_t + b_{i2}DEF_t + b_{i3}TERM_t + b_{i4}TB_t + b_{i5}iTraxx)r_{mt+1} + \varepsilon_{it+1} \qquad (9)$$

And with the fitting for the betas being based on those results

$$\widehat{\beta_{it}} = \widehat{b_{i0}} + \widehat{b_{i1}}DIV_t + \widehat{b_{i2}}DEF_t + \widehat{b_{i3}}TERM_t + \widehat{b_{i4}}TB_t + \widehat{b_{i5}}iTraxx \qquad (10)$$

The equations for the conditional market regressions later performed is the same as those used in fitting the conditional betas. We use these betas in the sorting procedure described below. Throughout the paper, we use the iTraxx index divided by 1000, in order for it to have a similar order of magnitude as the other variables in the regression.

The Petkova and Zhang sorting procedure is then performed in order to study the variation of the betas with respect to the fluctuations in the expected market risk premium. The procedure is performed in order to remove a large portion of the market noise and see how the betas vary during the different market conditions. Sorting on the same classification as Petkova and Zhang, i.e. Peak (Lowest 10% of the expected market risk premium), Expansion (Below average), Recession (Above Average), Trough (Top 10% of the expected market risk premium), we take the average of the conditional betas for each segment.

To verify statistical robustness of the results in the calculations and sorting procedure of the conditional and fitted betas, the generalized method of moments (GMM) is performed in addition to the method described above (not reported). GMM is used in order to eliminate estimation error and avoid biases and potential interferences in the calculations of the beta premium sensitivities. We find that the betas of both tests move in the same direction. With the betas of both tests going in the same direction, we consider the robustness of our initial results to be sufficient and elect to use those results in our study rather than to include the GMM output.

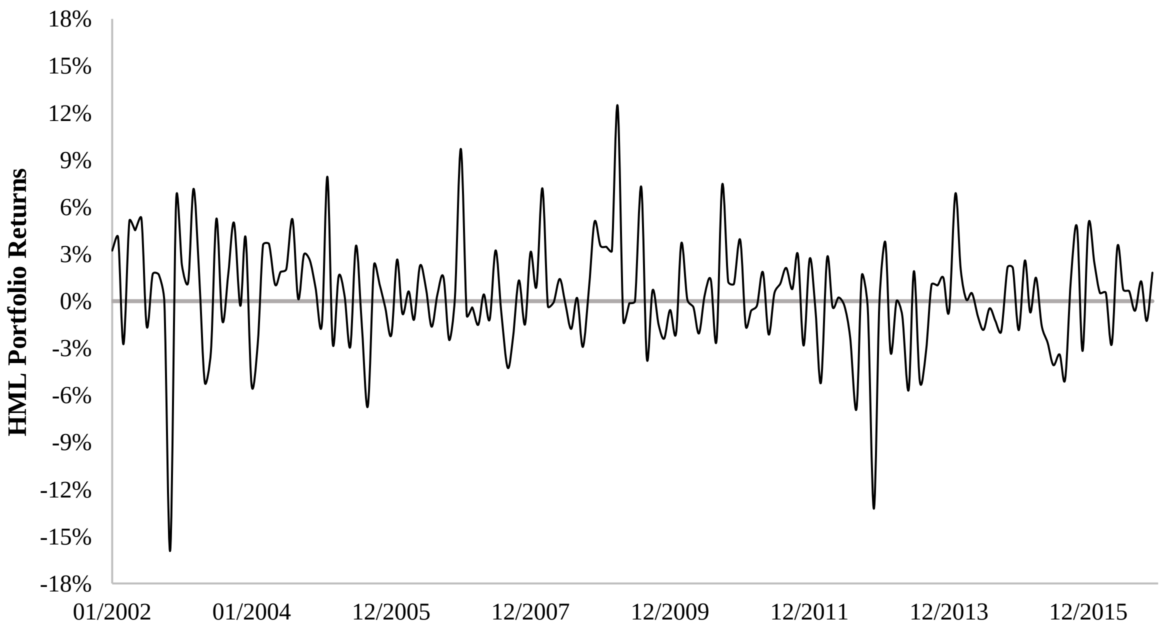
We then examine the conditional CAPM's ability to capture the returns and to study if alpha decreases in the conditional market regressions using the fitted betas. We perform two runs of these test, both with and without the inclusion of disaster proxy. Although we elect to use the conditional CAPM and not the consumption CAPM that Bai et. al. use in their paper, the addition of our disaster proxy is motivated from the implications that can be drawn from their paper. In short, we test if disaster sensitivity helps in explaining the variation in the premium.

Having replicated Petkova and Zhang's method with the inclusion of our disaster variable, the variable's explanatory power in regard to the movements in the HML portfolio betas is then tested. If the disaster variable has explanatory power, we would expect strong significance, and with regards to how a credit default swap index typically react during disasters, a positive coefficient for the index. This stems from how insurance contracts, like a credit default swap, traditionally become more expensive during periods of financial turmoil. This results in the index rising and leading to a positive coefficient as the portfolio betas also increase during periods of financial turmoil.

4. Results

4.1 The Premium

The value premium is first studied for the entire period of 2002 – 2016, and then divided into smaller predefined intervals in order to examine the premium's development under different conditions. This decision is made with consideration to the fact that our overall time frame captures a financial disaster, allowing for the study of the premium pre- (01/2002-04/2007), mid- (04/2007-12/2008) and post-crisis (12/2008-12/2016). We then study the implications of accounting for time-varying risks both with and without our disaster proxy and the ability of the method in capturing portfolio returns. Finally, we test how well the disaster proxy performs in capturing the movements happening in the HML portfolio betas. We find that the portfolio, over the entire period of 2002-2016, has positive return of 0.41% ($t = 1.59$) per month. For the total period, we find an alpha of 0.22% ($t = 3.08$) allowing us to reject the null hypothesis that alpha is indifferent from 0. **Graph 1** shows a graphical representation of the variation in the HML portfolio returns.



Graph 1: The graph above presents the returns of the HML Portfolio

4.1.1 Pre-Recession

For the pre-recession period, defined as 01/01/2002 - 01/04/2007, the portfolio generates a mean monthly return of 0.88% ($t = 1.82$) and an alpha of 0.95% ($t = 10.16$). These results show that both the premium and the puzzle exist in Sweden for the period preceding the subprime crisis. Our results, in this regard, are in line with most findings - including that of the original papers on the topic (Fama & French, 1992; Rosenberg et. al., 1985). The existence of the premium during expansive markets is rather expected and well documented within the existing literature, and our results do not suggest anything different.

4.1.2 Recession

The recessionary period, 01/04/2007 - 31/12/2008, is then isolated in order to study the variation of the premium during the crisis. The literature suggests that returns must act as a compensatory factor for investors taking on additional risks in holding the assets (Fama, 1970). Although Fama and French themselves did not argue explicitly to what risks investors are exposed to by holding the HML portfolio (Fama & French, 1992), authors have proposed the idea that the premium acts as a compensatory factor mainly for the disaster risk exposure of value stocks (Bai et. al., 2019; Lee et. al., 2014) (although through several different suggested risk passages (Zhang, 2005; Cao, 2015; Fama & French, 1992)). If value stocks are exposed to higher risks, we should see a decrease in the premium during the subprime crisis.

During this timeframe, the mean monthly HML portfolio return decreases to 0.34% ($t = 0.59$). The implication of the t-stat is that the null hypothesis ($H_0: R_{HML} = 0$) can not be rejected under a $-2/+2$ t-test and that the returns cannot be said to significantly differ from zero. The monthly portfolio alpha is 0.06%, which shows that the alpha has decreased to levels very close to 0. These results satisfy the disaster risk compensation explanation as we see the previously positive and significant results revert to values not significantly different from zero during the subprime crisis. In other words, investors are receiving higher returns during an expansive market as compensation for taking on disaster risk. This provides further incentives to study the effects of time-varying risks in explaining the returns.

4.1.3 Post-Recession

Looking at the period post-recession, defined as 31/12/2008 - 31/12/2016, we find a smaller, rather insignificant, premium of 0.11% ($\mathrm{t} = 0.32$) and an alpha of -0.22 ($\mathrm{t} = -2.21$). The results during this period are in line with recent research suggesting that financial anomalies generally, and the value premium specifically, have recently diminished in statistical significance (Cotter et. al, 2018). The underlying factors for this decrease could be many but the contemporary literature suggests that the risk hypothesis holds. Investors are receiving lower risk compensation due to the assets being less exposed towards the risks compared to what they previously were. The decreased risk compensation could portray itself due to the riskiest firms going bankrupt, firms restructuring their overall business to be less exposed to the costly reversibility of investments as suggested by Zhang (Zhang, 2005), or simply by taking on less leverage (Cao, 2015). This argument for lower risk compensation is backed up by the literature surrounding the capital structure effect of the recession (Bliss et. al., 2015). Financially restricted firms were hit the hardest during the subprime crisis, and had their returns decrease substantially compared to other less restricted firms (Lee et. al., 2014). The literature suggests that, of the firms classified as value firms, the most restricted firms affected the portfolio returns the hardest (Lee et. al., 2014). This indicates that Cao's argument about capital structure risk is a strong reason for the premium's existence. Unlike their peers, financially restricted firms would be unable to internally compensate by hoarding cash (Bliss et. al., 2015), driving them to bankruptcy. If the value portfolio loses the riskiest firms that previously produced the highest returns, then we would expect a shrinking premium due to lower risk compensation being required by investors as the value portfolio now has a lower risk than it did previously.

The variation of the premium and the puzzle throughout our entire interval is best shown graphically. In **Graph 2** the overall alphas for the portfolio vary throughout the time-period with the highest alpha being documented during the period preceding the recession. The portfolio alpha then decreases during the subprime crisis, corresponding with the increased beta values as shown graphically in **Graph 2**. The betas are indicating an increased market exposure for the portfolio. The decreased alpha that is documented in the period after the recession is also a product of increased beta values.

Graph 2: The graph above presents the alpha of the HML portfolio (Dashed) graphed versus the values of the rolling (24 month window) beta for the HML portfolio (Solid)

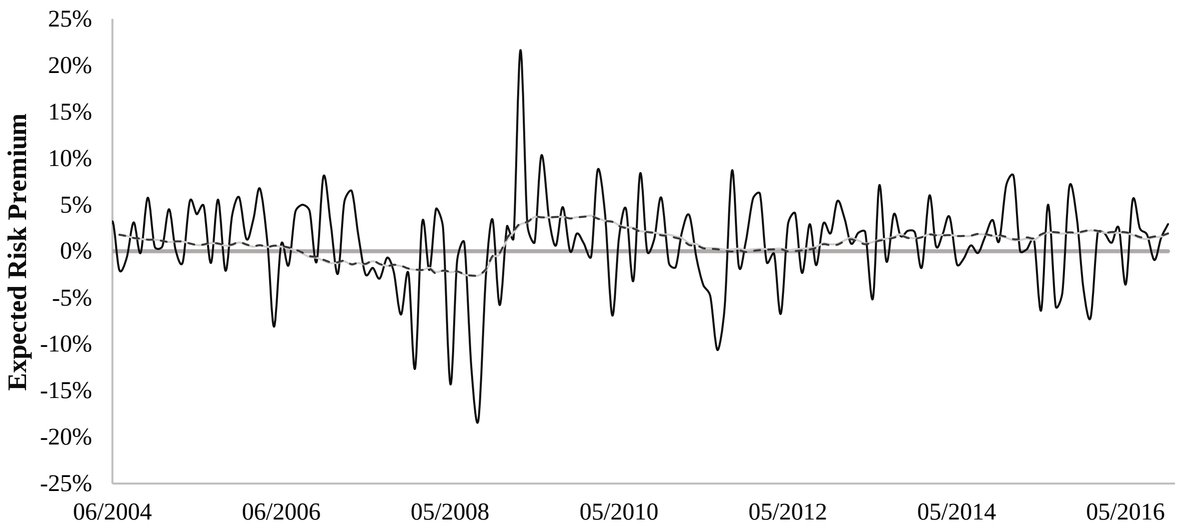
To conclude our discussion of the variation in the premium we note that, in our sample, the portfolio betas are initially low when the portfolio returns are high (in other words the opposite of what the CAPM needs to capture the returns similar to what Fama and French found in their 2006 paper (Fama & French, 2006)), which shows the value puzzle's existence within our region. Betas begin to indicate increased systemic exposures, through higher values, during the subprime crisis. This increased systemic exposure is maintained even throughout the post-recession period where the initially lower betas quickly turn upwards to positive values. These results are supported by Andrea Frazzini and Lasse Pedersen's paper, Betting Against Beta (Frazzini & Pedersen, 2014). The negative correlation between the asset beta and its alpha indicates that value stocks are more exposed to the market conditions during downturns, as it has been established that value stock betas display a countercyclical pattern (Fama & French, 1992; Petkova & Zhang, 2005). This causes the portfolios to underperform during those downturns.

Overall, the entire period captures the known phenomenon of a strong and existing value premium and the CAPM's failure to explain it. Following John Cotter and Niall McGeever's process of interpreting anomalies (Cotter & McGeever, 2018), we determine the next steps required in analyzing this premium. The value premium is a persistent financial anomaly that is non-spurious, as it has been heavily studied over time and proven to be significant by many researchers. The premium is also unlikely to be a result of market inefficiencies since market restrictions and trading costs are generally equal between trading value and growth stocks. As a result, we are left with one main option to investigate, which is this anomaly being compensation for the carried risk that the CAPM does not account for.

4.2 Expected Market Risk Premium

Having drawn our conclusion about premiums existence and the Capital Asset Pricing Model's failure to explain it during portions of our defined interval, we then turn towards the possibility of time-varying risk explaining the excess return. Petkova and Zhang's paper proposes the idea that the conditional betas may be a more suitable measure for a portfolios risk exposure compared to the unconditional betas that the Sharpe-Lintner CAPM uses. As previously mentioned, the realized market excess return is a noisy measure of the overall market conditions which Petkova & Zhang argue makes for misleading conclusions. More precise measurement of the aggregate economic condition, and thus the (expected) risk premium within the market, is a function of the default spread, term spread, and short-term interest rate as well as the dividend yield within the economy. These variables act as better predictors than the realized market return, and are all commonly used factors in the modeling of the expected market risk premium. The excess market return $(\mathrm{r_m} - \mathrm{r_f})$ is regressed on the lagged conditioning variables with the expected risk premium being the fitted component retrieved from the regressions performed, as shown in **Equations 3 & 4**. The two fittings of the expected market risk premium are plotted together with the realized market excess return in **Graph 3**. As discussed in the methodology, we do not expect the inclusion of the iTraxx to largely affect the expected equity risk premium. This can be seen in how the two series overlap to a large extent.

Our results indicate that the expected market risk premium rises during periods of financial turmoil (such as the subprime crisis of 2008) confirming that the metric acts as a countercyclical measure of the overall economic conditions - in other words, the expected market risk premium is high when the price of risk is high. Our results are presented graphically in **Graph 3**. Jessica Wachter concluded in her paper (Wachter, 2013) that increases in the market risk premium flow via changes in the aggregate consumption within an economy. Modeling the expected risk premium with the inclusion of our disaster variable should enable the capturing of the implications of Bai et. al. even when using the conditional CAPM.



Graph 3: The graph above presents the two series of Expected Risk Premium (with (Solid Grey) and without (Dashed Dark Grey) our disaster proxy) graphed together with the market excess return (Grey Line)

4.3 Beta Sorting and Sensitivity

Having concluded that the equity risk premium acts as a countercyclical variable, the sorting procedure is performed on both the fitted (conditional) betas and the 24-month rolling betas. The results indicate that, when accounting for time-varying risk, the conditional model predicts higher market exposure for the HML portfolio compared to the CAPM as shown in the higher betas. In line with the results of Petkova and Zhang, we find that the HML betas are higher during periods of financial distress when the equity risk premium is high. The rolling betas, conditional betas, and the conditional betas calculated using GMM (not reported) all go in the same direction with higher values during periods of turbulent conditions. Our beta values, rounded to three decimals, are presented in **Table 1**.

	Peak	Expansion	Recession	Trough
Fitted Beta	0.785	0.852	0.903	0.967
Fitted Beta w/ Disaster	0.579	0.629	0.710	0.709
Rolling Betas	-0.042	-0.020	0.235	0.211

Table 1: Conditional and rolling (24 month) betas sorted by the expected market risk premium into four states: Peak (bottom 10% of premium), Expansion (below average), Recession (above average), Trough (top 10% of values).

The main takeaway from the usage of the conditional CAPM is its ability to explain risk exposure via beta premium sensitivity. After regressing the conditional betas on the expected market risk premium, we find positive beta premium sensitivities similar to the results of Petkova and Zhang. Following Petkova and Zhang's method, our regressions show a beta premium sensitivity of 3.56 ($t = 5.67$) for the overall timeline indicating that additional downside exposure is a factor in the premium.

The regressions are then re-run with the inclusion of the disaster proxy. In those regressions, the beta premium sensitivity decreases compared to our initial regressions to 2.90 ($t = 3.77$). The fact that both of the calculated sensitivities are significantly positive is the main takeaway as it indicates larger risk exposure for the HML portfolio when the price of risk is high.

4.4 Conditional Market Regression

The possibility of time-varying risk capturing the premium, studied via regressing the excess HML returns on the conditioning variables and the excess market return, is then finally assessed. For the overall time-period, we note an alpha equal to zero. This stands in contrast to the positive alpha component that was found using the CAPM with 24-month rolling betas. The output from the regression is presented in **Table 2** below.

Excess HML Return	Coefficient	Standard Error	t	P>|t|
$\boldsymbol{r_m - r_f}$	-0.79	0.40	-1.97	0.05
DEF $*$	-15.42	12.38	-1.25	0.22
$\boldsymbol{DIV}$ $*$	26.40	14.12	1.87	0.06
TB $*$	52.07	76.36	0.68	0.50
TERM $*$	21.39	11.73	1.82	0.07
Constant	0.00	0.00	-0.10	0.92
$\boldsymbol{Prob > F = 0.0031}$	$\boldsymbol{R^2 = 0.116}$	$\boldsymbol{Adj. R^2 = 0.085}$		

Table 2: The lagged values of the respective conditioning variables are multiplied with the excess market return (indicated by a $*$) in order to provide the dataset for the conditional market regressions (**Equation 7**). We regress the excess HML returns (returns over the risk-free rate) on the conditioning variables and the market excess return. Where $\boldsymbol{r_m - r_f}$ = Excess market return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-free rate, TERM = Term Spread,

The output of the second run of the regression, with the inclusion of the iTraxx index as another variable in the fitted betas, is presented in **Table 3**. We find that the explanatory power of the regression increases by around 11.2% ($R^2 = 0.129$ compared to $R^2 = 0.116$) with the iTraxx variable being significant ($t = -1.47$).

Excess HML Return	Coefficient	Standard Error	t	P>|t|
$r_m - r_f$	-0.59	0.42	-1.39	0.17
DEF $*$	-13.71	12.39	-1.11	0.27
DIV $*$	35.29	15.31	2.30	0.02
TB $*$	-17.24	89.48	-0.19	0.85
TERM $*$	15.43	12.37	1.25	0.21
iTraxx $*$	-3.63	2.48	-1.47	0.14
Constant	0.00	0.00	-0.01	0.99
$Prob > F = 0.0027$	$R^2 = 0.129$	$Adj.R^2 = 0.093$		

Table 3: The lagged values of the respective conditioning variables (including our disaster variable) are multiplied with the excess market return (indicated by a $*$) in order to provide the dataset for the conditional market regressions (**Equation 9**). We regress the excess HML returns (returns over the risk-free rate) on the conditioning variables and the market excess return. Where $r_m - r_f$ = Excess market return, DEF = Default Spread, DIV = Dividend Yield, TB = Risk-free rate, TERM = Term Spread, iTraxx = iTraxx Index

The implication of these results is that the conditioning variables perform well in capturing the returns but that more of the variation in excess HML returns is captured with the inclusion of our disaster proxy. The iTraxx index achieves a higher significance in our test than most of the traditionally used conditioning variables. This goes in agreement with our hypothesis based on the paper by Bai et. al, where accounting for disaster risk is significant in explaining excess HML returns.

4.5 HML Betas & Explanatory Power

The disaster variable's explanatory power over the movements in the HML betas is tested by regressing the betas on the conditioning variables. The output of those regressions is presented in **Tables 4 & 5** below.

HML Betas	Coefficient	Standard Error	t	P>|t|
DIV	-12.20	3.37	-3.62	0.00
DEF	10.42	2.58	4.04	0.00
TERM	-11.99	2.64	-4.54	0.00
TB	-156.85	16.88	-9.29	0.00
Constant	0.63	0.10	6.17	0.00
$Prob > F = 0.0000$	$R^2 = 0.400$	$Adj.R^2 = 0.384$		

Table 4: The 24-month rolling beta is regressed on the set of conditional variables. Where DIV = Dividend Yield, DEF = Default Spread, TERM = Term Spread, TB = Risk-free rate

As expected from Petkova and Zhang's study, all the conditioning variables are highly significant, with the regression explaining around 40% of the variation of HML Betas. The inclusion of the iTraxx in the regression increases the R^2 in our tests with the disaster variable being significant ($\mathrm{t} = -2.2$). Adding the iTraxx index, we initially expect that this disaster proxy would have a positive coefficient, given how the pricing of insurance instruments, such as a credit default swap index, reacts to periods of financial turmoil. However, the negative coefficient we find in the regression gives incentives for further testing.

HML Betas	Coefficient	Standard Error	t	P>|t|
DIV	-9.34	3.58	-2.61	0.01
DEF	11.70	2.61	4.48	0.00
TERM	-13.74	2.73	-5.04	0.00
TB	-177.92	19.22	-9.26	0.00
iTraxx	-1.25	0.57	-2.20	0.03
Constant	0.69	0.10	6.60	0.00
$\boldsymbol{Prob > F = 0.0000}$	$\boldsymbol{R^2 = 0.420}$	$\boldsymbol{Adj. R^2 = 0.400}$		

Table 5: The 24-month rolling beta are regressed on the set conditional variables including the addition of our disaster variable. Where DIV = Dividend Yield, DEF = Default Spread, TB = Risk-free rate, TERM = Term Spread, iTraxx = iTraxx Index

The test is re-run using the iTraxx crossover index which incorporates additional high-yield credit default swap prices in the calculations of the index levels. We run the test for the iTraxx crossover index's relatively short existence of 10/2011 - 12/2016 and rerun the test for the main iTraxx index over the same time period. We find that the iTraxx Crossover index yields a positive index coefficient ($\mathrm{t} = 1.61$), while the main iTraxx index still produces a negative coefficient. Finally, we run a regression with both the iTraxx main and the iTraxx Crossover for the same time-period. We find that the coefficient signs remain intact and that both proxies are very highly significant ($t = -3.72, t = 3.04$ respectively), with the model capturing around 73% of the variation in the HML Beta.

Our initial argument about using the iTraxx main index, and why the high-yield index was not used, to begin with, is the fact that the index captured our entire desired time-period well and provided data on the insurance market of credits - a field sensitive to disasters. In other words: The iTraxx high-yield credit default swap index did not exist during the subprime crash meaning the disaster exposure for the period could not have been measured using that index. Our conclusion from these results is that we capture the "flight to safety" aspect of the financial markets. During periods of financial turmoil, or disaster events, investors often "flee to safety" by purchasing both more liquid assets (flight to liquidity) but also to assets of higher quality (flight to quality). Investors move funds from junk-level credits into investment grade credits due to the innate higher stability of such credits (Bethke et. al., 2017). The different coefficients could thus capture the known "flight to quality" behavior of investors, meaning that the differing coefficients between the indexes does not alter the overall conclusion of disaster risk being priced into the premium. The "flight to quality" phenomenon was especially strong during the subprime crisis and is heavily correlated with investor sentiment (Bethke et. al., 2017).

Our results indicate the movements within the iTraxx index is highly correlated with the portfolios market sensitivity, showing that the correlated movements between the portfolio returns and the market returns can be predicted by the disaster proxy. This relationship gives weight to the proposal that disaster risk is priced into the premium. The iTraxx index thus significantly increases this model's explanatory power by 5% ($R^2 = 0.420$ compared to $R^2 = 0.400$). Although this may seem like a small number, it is in fact economically important as a step in explaining the value premium, one of the most persistent anomalies in finance.

5. Implications and Conclusions

Incorporating the risk for disasters takes us a step closer towards explaining the value premium puzzle. We start by finding a significant value premium over our desired interval, 2002 - 2016. This premium varies during the interval, where we document a positive and significant value-premium for the period preceding the subprime crisis that then shrunk to values not significantly different from zero during the subprime crisis. We find similar variation in the alphas of the HML portfolio, with a significantly positive alpha pre-crisis, a non-significant alpha during the crisis, and a significantly negative alpha post-crisis. The Sharpe-Lintner CAPM found low market sensitivities when looking at the rolling, unconditional, betas. These findings act as the main reasons behind the high portfolio alphas that were documented and as an underlying reason for the value premium puzzle's existence during the expansive market conditions leading up to the recession. Although low betas are to be expected of a long/short investment strategy such as the HML portfolio, the comparatively low rolling beta during expansive market conditions that shifted upwards during recessions adds weight to the disaster risk exposure argument.

In the study of time-varying risk, the fitted betas are sorted on the expected market risk premium. We find larger (positive) fitted betas for all four different market conditions (Peak, Expansion, Recession, and Trough). We find that the highest market sensitivity of the portfolio is during periods of financial distress or, in other words, where the expected market risk premium is the highest. The results using both unconditional and fitted betas, as well as our robustness checks using GMM, all go in the same direction in explaining higher betas when the expected market risk premium is the highest.

Rising betas during "trough" periods indicate a larger exposure to the systematic risks at a time when the price of risk is high. The implications from the movements of the betas are backed up in the results surrounding the beta premium sensitivity as presented by the conditional CAPM. The positive beta premium sensitivities are achieved both with and without the inclusion of our disaster variables.

In our test of the time-varying risk explanation, using conditional market regressions both including and excluding our disaster proxy, we find strong explanatory power with an alpha component that is not significantly different from zero. Our conclusion from these results is that time-varying risk exposure plays a role in the returns and that we can capture the premium's variation during our defined time-interval. The inclusion of the iTraxx index in the tests shows that the variable has high significance, indicating that the disaster exposure is priced into the value premium.

The addition of the disaster variable decreases the alpha component for our tests: We find a monthly alpha of -0.003% ($t = -0.01$) in our conditional market regression including iTraxx and a slightly higher -0.02% ($t = -0.1$) using only the original conditioning variables. Although both alphas are statistically insignificant and conclusions cannot be completely drawn from them alone, we see that the inclusion of our disaster risk proxy goes in the right direction in decreasing the constant. In the study of the variable's explanatory power over the movements in the HML portfolio betas, we find that the iTraxx main index is significant ($t = -2.2$) and increases the explanatory power of the test. However, contrary to what we had initially expected, the variable holds a negative coefficient. The test was re-run for the period 10/2011 - 12/2016 with both the iTraxx Main index and the iTraxx Crossover index, which includes more high-yield credit defaults swaps than the main index. The iTraxx Main index maintains its negative coefficient while the iTraxx Crossover index produces a positive and significant coefficient. We conclude that the differing coefficients are the results of investors fleeing from high-yield credits to investment grade credits during periods of financial distress. In other words, the differing coefficients can be attributed to the "flight to quality" reaction of investors which was especially strong during the subprime crisis.

Overall, we attribute our results to the arguments about the driving factors of the premium. Viet Cao (Cao, 2015) argues that financial leverage acts as a main driver for the premium, together with the investment irreversibility channel proposed by Lu Zhang (Zhang, 2005). With the more financially constrained firms being unable to internally compensate the supply shock to the capital markets (Bliss et. al., 2015), it affects the returns of the value portfolio more than that of the growth portfolio. With the premium being inversely related to size (Fama & French, 2011) and the capital structure effect hitting smaller firms the hardest, we argue that the smaller premium after the crisis reflects capital structure decisions and thus a lower risk compensation to investors. Simply put, the disaster risk of value stocks has decreased.

Overall, our results regarding disaster risk being priced in has statistical significance and has implications for investors attempting to take advantage of the value premium. Investors are in fact being compensated for taking on additional risks, meaning that the HML factor as laid out in Fama & French's original paper, captures compensation for the added exposure.

Although our results with regards to the disaster variable are statistically significant, further research on the topic could be pursued on additional disaster proxies. Also, tests could be conducted over a longer period by leveraging indexes that date further back. For example, Bank of America has multiple high-yield indexes with start-dates as long back as 1996 (e.g. BofAML US High Yield B Total Return Index) allowing for a longer study in order to see if the results are comparable and as significant. Additionally, since different countries' capital markets may have different sensitivities to worldwide disasters, a possible improvement of our study can be to apply our tests on a wider number of countries to test if the results are as significant.

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