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TIME-VARYING TAIL RISK IN THE FINANCIAL SECTOR

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Abstract: This paper investigates the usefulness of time-varying tail risk in the financial sector. The findings of this paper support the notion that financial sector time-varying tail risk possesses predictive power over future market returns over a horizon of one-month, one-year, three-years and five-years and some predictive power over future financial crises. Within the financial sector there are four industries recognized; the banking, insurance, broker dealer and other industry. These industries all have a different level of systemic risk and thus pose different risks to the financial sector and in term to the real economy.

Keywords: Tail risk, time-varying, financial sector, Hill alpha, predictor

1 Introduction

In sight of the financial crisis that started a decade ago there are still a lot of questions unanswered about how to prevent a future crisis from happening. This crisis clearly showed that a downturn in the financial sector can impose negative externalities on the real economy. As an example in the US the unemployment rate increased by five percentage points during the financial crisis (Hurd and Rohwedder, 2010). A downturn such as in the crisis of 2008 throughout the full financial sector is an extreme event. Therefore, to prevent future crises from happening or to soften the blow from a crisis it is important to find an efficient measure to predict extreme events in the financial sector. In this paper a time-varying tail risk estimate is used to measure systemic risk in the financial sector. I argue that systemic risk can be at the baseline of a financial crisis and knowledge about this risk is vital to the implementation of regulation in the financial sector. In this paper systemic risk is defined as the risk of the financial sector as a system. That is, the risk of a system wide crisis which is initiated by spillover effects of one or more financial institutions facing difficulties, to other financial institutions.

Thus, the challenge tackled within this study is to propose a financial sector time-varying tail risk measure that can predict future events regarding market returns and financial crises. This predictor could be used by regulators to act in advance to downplay the negative results consistent with a weak real economy and a financial crisis. A focus is put on the financial sector in specific as the structure of this sector enlarges the probability of a systemic event happening due to the composition of the balance sheets of financial institutions and the close tie between financial institutions and the rest of the economy. Therefore, the central statement for the problem at hand is: *'What is the influence of financial sector time-varying tail risk on future market returns?'*

In order to measure the time-varying tail risk, institution-level price crashes are exploited every month to identify common fluctuations in tail risk among individual financial institutions. The goal is to estimate the time-varying tail risk of the entire financial sector at each point in time. The intuition behind the model is that tail risk of individual financial institutions is closely related to the aggregate tail risk of the entire sector. Therefore, the data of the entire financial sector can be used to predict systemic risk throughout the sector. I expect that the Hill measure will be a valuable predictor of future crises and of future market returns. Given that it is expected that the time-varying tail risk in the financial sector has predictive power, it is of interest to compare the moments of financial crises with the time-varying tail risk measure. The value weighted market return, GDP growth, industrial production and unemployment can be used as indicators of a financial crisis to investigate the correlation between the time-varying tail risk and a poor economic environment. This leads to the following sub question: '*Can an economic downturn be predicted by the time-varying tail risk of the financial sector?'*

The time-varying tail risk measure can be further explored by dividing the financial corporations into four different financial industry groups. The different financial industry groups will be defined following the definition Brownlees and Engle (2016) use in their research. They will be divided into banks, insurance, broker-dealers and others. Leading to the following sub question: '*Is there a difference in the time-varying tail risk measure between the different financial industries; depositories, insurance, broker-dealers and others?'*

Another sub question arises due to the characteristics of the Hill estimator. Namely, the fact that the Hill estimator assumes that stock returns are fat-tailed and does not consider the possibility of normally distributed stock returns at a certain point in time. This could lead to overestimating the probability of a tail risk event happening. Therefore, it is interesting to investigate the difference between the Hill estimator and another more general tail-risk estimator that allows for normal distributions as well as fat-tail distributions. In this paper I investigate the Dekkers, Einmahl and de Haan (DEDH) estimator to ensure the stocks in the sample follow a Pareto distribution. If they do not follow a Pareto distribution the DEDH estimator is a more appropriate measure to use. Hence, the following sub question arises: '*Is the Hill estimator the appropriate tool to use to calculate time-varying tail risk?'*

The academic contribution of this research is to provide an insight into the usefulness of time-varying tail risk of the financial sector as a predictor of weak economic conditions or a financial crisis. This research will provide a share in the discussion of useful tools to predict crises and it will increase the knowledge about systemic risk in the financial sector. The findings of this paper indicate that the financial sector Hill estimator is a good predictor for future market returns and the estimator contains some predictive power over a future economic downturn. Notably, the DEDH estimator proofs that until now the Hill estimator is the appropriate tool to calculate the time-varying tail risk in the financial sector and its industries, as the stock returns follow a Pareto distribution. The Hill measure calculated for the different industries proves that systemic risk for the banking, insurance, broker dealer and other industry are different and vary over time, with the banking and insurance industries displaying the highest level of systemic risk..

In section two previous literature about tail risk is discussed. Thereafter, in section three the time-varying tail risk measure is introduced. In addition, the methodology and assumptions are discussed as well as the sample and the data used. In section four, the empirical results and implications are analyzed. Then in section five the results from section four will be discussed. Lastly, in section six a conclusion is drawn and suggestions for future research are discussed.

2 Literature Review

My research question draws on several strands of literature. Like most of the former research performed on systemic risk, I look at extremes to predict systemic events. This research is in line with the extreme value theory, which essentially models intermediate-level observations that are close to extremes and extrapolates the observed properties into an extreme level. This indicates that a systemic crisis can be approximated by the interconnectedness of tail events, of which the observations are not necessarily at a crisis level (Zhou, 2009). To be able to properly investigate the usefulness of systemic risk as a predictor it is important to understand the concept. There are several slightly different definitions of systemic risk mentioned in literature, but in this paper, we follow the definition as described by de Bandt and Hartmann (2000). They argue that at the very basis of systemic risk is the notion of contagion working from one institution, market or system to the others. Thus, at the heart of systemic risk in the financial sector is the interconnectedness of all the different financial institutions.

A similar research about time-varying tail risk has been conducted by Kelly and Jiang (2014). However, they include the whole stock market, whilst this paper will focus solely on the financial sector. The novelty of their study is the fact that they consider a risk factor that is not constant over time but instead is time-varying. Their main finding is that the time-varying tail risk measure is highly persistent and has strong predictive power for aggregate stock market returns for horizons from one month to five years. Another important finding from their research is that the time-varying tail risk is performing at least as well as similar measures considered in previous literature. Thus, the conclusions of their paper provide the building blocks this research is built upon. The approach relies on the assumption that corporations have different unconditional tail risk, but the dynamics of their tail risks are similar. Their findings support this assumption.

Several researches on extremes have been discussed in recent literature that investigate systemic risk as a predictor of a financial downturn. Most of the literature about systemic risk measures can be divided into two kinds of measures, the first group are the measures related to Value at Risk (VaR) and the second group are the measures related to expected shortfall (ES). The literature has in common that they all find that systemic risk measures are valuable as a predictor for systemic crises and financial crises happening. Even before the financial crisis of 2008 there is research that pointed out the importance of systemic risk in financial systems.

In this paper the systemic risk estimate is calculated for the financial sector. Previous research has discussed several reasons why it is interesting to look at the financial sector in specific. First of all, it is claimed that to be able to grasp the foundations of a financial crisis you have to start by integrating systemic events in banking and financial markets (Bandt and Hartmann, 2000). In the financial sector the different institutions are interconnected through several means. Mainly the fact that banks put loans at other banks increases the risk of spillover effects in case of an extreme event happening at one bank. This phenomenon is called systemic risk, the risk of other banks failing due to the failure of one bank. Additionally, there is evidence that when the financial sector is facing difficulties, these hard times will spill over to firms in other sectors. Intuitively this makes sense as financial institutions are at the heart of financing, investments and thus of growth. Next to this fact, they are also strongly involved in the payment system and monetary means. Since if the financial sector tightens, they will decrease the credit supplied, which in term leads to higher default rates under institutions that are not able to roll over current debt (Pereira and Rua, 2015). To these reasons De Bandt and Hartmann (2000) add that the interconnectedness of the interbank money market makes the financial system more vulnerable as well as the information intensity of financial contracts and related credibility and uncertainty issues. Moreover, as nowadays market is becoming increasingly interconnected because of the global environment and the progression of technology the impact of systemic risk is becoming increasingly important, especially as the level of systemic risk is increasing over time (Straetmans and Chaudry, 2015). There, however, is also a positive effect of the failure of one financial institution to the other financial institutions as it will provide them with strategic gains from the acquisition of the failed institution's business (Acharya, 2009).

Within the financial sector I will look at four different sectors; banks, insurance companies, broker-dealers and others. Evidence for this division is given by Billio et al. (2012) who find that banks, and in second place insurance companies, have a more important systemic role. On the other hand, Acharya et al. (2010) find that depository institutions and insurance institutions face lower absolute levels of risk. Thus, in this research I will look at what industry group will have the largest time-varying tail risk.

As the time-varying tail risk measure can be a useful predictor for a financial crisis, regulations could be adapted in such a way as to take advantage of the knowledge gained. Regulators can take preventive actions based on an expected systemic crisis arising. Regulations are imposed to soften the concerns about large social and economic costs caused by a systemic crisis. Nonetheless, as de Bandt and Hartmann (2000) argue a systemic event in financial systems can also be efficient if it is able to eliminate just these players in the system that are inefficient, particularly when asymmetric information prevented the market mechanism from eliminating them. However, the elimination of those inefficient players does not take away the negative externalities imposed on the whole economy through the failure of those players. Thus, regulators need to consider taking actions to protect the rest of the economy as to forego the financial crisis spreading through the economy.

3 Research Design

3.1 Methodology

At the basis of the method used is the extreme value theory. Within this theory this paper investigates the Hill estimator varying over time as a measure of systemic risk. The use of the Hill estimator is replicated from the paper about tail risk and asset prices by Kelly and Jiang (2014). Just as in their paper, the time-varying tail risk will be calculated monthly by using a month of daily data to increase the available data points. Thus, the daily return data in one month is used to define the monthly extremes. More specifically, I compute the Hill estimator using the cross-section of daily returns from the financial sector.

(1.1) $$\text{Hill}: \frac{1}{\hat{\alpha}} = \frac{1}{m-1}\sum_{i=1}^{m-1} \ln \frac{X_{i,n}}{X_{m,n}} = \frac{1}{m-1}\sum_{i=1}^{m-1} \ln X_{i,n} - \ln X_{m,n}$$

α = Hill estimator; m = number of extremes used in the calculation; $X_{i,n}$ = a ranked log return observation

The Hill estimator used as a proxy for systemic risk equals the alpha in formula 1.1. To implement this formula the returns $X_{i,n}$ are ranked from largest to smallest as the extremes I want to look at are now positive as I used X = -R. Thus, when ranking the returns from largest to smallest we are looking at the losses. In this research I use a set level of m of five percent, which defines the threshold for the extremes used to calculate the Hill alpha. This estimator uses only those observations that exceed the tail threshold and discards non-exceedances. Thus, the extreme returns are defined as the set of ranked returns from $X_{1,n}$ to $X_{m,n}$. For our estimator it is crucial that not too many observations are used for the tail, such that some observations belong to the center rather than to the tail. It is preferred to not use all the available information over using the wrong information, which can be harmful to my results (Jansen and de Vries, 1991). This is due to the fact that whenever too many observations are used, and some do not belong to the tail, my estimator is underestimated. In this case, the data that belongs to the center of the distribution rather than to the tail will dominate the variance part. Moreover, it is also harmful to take too little observations as the possibility exists that a few extreme outliers dominate the results.

One advantage of this method is that it can be applied using strictly stock return data. It is convenient to use stock data since it is publicly available information and available at a high frequency. An important characteristic of stock returns is that they are fat-tailed in comparison with the normal distribution, as de Vries (2005) shows in his paper. Therefore, in this paper the Hill measure is used, which is designed for data with heavy tailed distributions. The advantage of using the methodology proposed in this paper to calculate the systemic risk measure is that it shows time variations. This enables you to identify the level of systemic risk a sector contains at each point of time. Another advantage of the proposed methodology is the high frequency at which the measure can be calculated. This high frequency is beneficial when the measure is used for preventive regulations.

3.2 Assumptions

First of all, my research centers on a tail distribution of returns. Similar to Kelly and Jiang (2014), I assume that the lower tail of asset return n behaves according to equation 1.2. Within equation

1.2 the lower tail distribution is defined as all the returns falling below the extreme negative threshold s. The shape of the tail is defined by $-\lambda_i/\alpha$, where λ_i is a constant and α may vary with the information set F_t. A high value of α indicates fat-tails and a high probability of an extreme event. Thus, α is the tail risk at time t and equals to the Hill alpha used in this paper as a proxy for systemic risk. Inherent in this formula is the assumption that stocks are driven by a common process with regards to tail risk indicated in the formula by α. Nonetheless, they can have a different level of tail risk, which is determined by the constant λ_i. Notably, the tail risk in the formula is constructed in such a way that it is following a dynamic power law.

(1.2) $$P\left(X_{i,t+1} < x \middle| X_{i,t+1} < s \text{ and } F_t\right) = \frac{x}{s}^{-\lambda_i/\alpha}$$

To calculate the time-varying tail risk of the financial sector individual stocks of financial institutions are used. This research assumes that the tail risk of an individual financial institution is closely related to the aggregate tail risk of the financial sector. Thus, that the tail risk of all the individual financial institutions share similar dynamics. Evidence for the similarity in tail risk within a sector is given by Kelly and Jiang (2014). This enables us to take the aggregate of tail risk across the sector to calculate the Hill estimator and pool the daily data of all the financial institutions to calculate the monthly Hill estimate. Thus, to measure the time-varying tail risk, institution-level price crashes are exploited every month to identify common fluctuations in tail risk among individual financial institutions. The goal is to estimate the time-varying tail risk of the entire financial sector at each point in time. Therefore, as the assumption is made that the tail risk of all the different financial institutions share similar dynamics, the data of the entire financial sector can be used to predict systemic risk throughout the sector. One important feature of the Hill estimator is that it assumes that the tail of the stock distribution obeys a power law as is shown in equation 1.2. This enables us to calculate the aggregate tail risk of the financial sector. Since when individual stock return tails obey a power law, the tail risk of these individual stocks will be inherited by, in this case, the tail risk of the financial sector (Kelly, 2014). Thereafter, the sum is taken of the data with power law tails, this sum is dominated by the variable with the heaviest individual tail.

I assume that the Hill estimator is an appropriate measure. One characteristic of this estimator is that it assumes that stocks of financial institutions always follow a fat-tail distribution. Nevertheless, it could be of interest to investigate other measures for tail risk that are not solely built for stocks following a Pareto distribution. Hence, I calculate the Dekkers, Einmahl and de Haan (DEDH) estimator following equation (2.1) which uses the generalized extreme value (GEV) distribution (Straetmans et al, 2008). The DEDH estimator can rightfully be calculated for stocks that follow a normal distribution as well as a Pareto distribution. This could be of interest as stock returns could have followed a normal distribution in the past and there is a possibility that future stock returns will follow a normal distribution. In case an estimator is used that is designed for heavy tails, but the distribution displays normal tails the estimator will be overestimated. In equation 2.1 the Hill estimator is used as an input as $M_n^{(1)}$ is the inverse of the Hill alpha. The question arises if you could not always use the more general DEDH estimator. However, as Straetmans et al. (2008) explain in their paper the generalization of the DEDH model goes at the expense of estimation risk. The DEDH estimator is not as precise as the Hill estimator is in case of a Pareto distribution and the DEDH-estimator can be used as a check as to whether the stocks used in the calculations follow a Pareto distribution. To calculate the DEDH estimator the same inputs are used as for the Hill-estimator and m is set at the five percent level for the extreme threshold.

$$\hat{\gamma} = M_n^{(1)} + 1 - \frac{1}{2}\left\{1 - \frac{(M_n^{(1)})^2}{M_n^{(2)}}\right\}^{-1} \tag{2.1}$$

with $$M_n^{(1)} = \frac{1}{\hat{\alpha}} = \frac{1}{m}\sum_{j=0}^{m-1} \ln(\frac{X_{n-j,n}}{X_{n-m,n}})$$

and $$M_n^{(2)} = \frac{1}{m}\sum_{j=0}^{m-1} \left(ln\left(\frac{X_{n-j,n}}{X_{n-m,n}}\right)\right)^2$$

The investigation of the DEDH estimator is especially interesting due to the limited data availability. As there is only data available from the 1960s and the growth in the stock market has not yet reached its limit nor has it been around for a long enough time to become stable. Especially in today's ever changing environment due to technological developments and globalization little can be said about the future distribution of stocks.

3.3 Sample

An important aspect of extreme events is that they occur infrequently. Consequently, we need a sufficient amount of data points to include enough extreme events (Kelly, 2014). The data in this research consists of 1357 US stocks of financial institutions obtained from Bloomberg for a timeline from 1980 to 2017. Over time the amount of data increases, which provides me with a varying amount of data over time, but mostly there are about 900 financial institutions considered at each point in time. I follow Kelly and Jiang in the sense that I take daily data and observe downfalls on a monthly basis. This provides me with approximately 30 times as many data points at every point in time. The sample of the financial sector contains active institutions as well as defaulted institutions. It is important to include defaulted institutions as these institutions are likely to be involved in a past systemic crisis and therefore they are an important predictor of this past systemic crisis. This means that these financial institutions are likely to be found in the tail of the distribution of the full financial sector. Moreover, if financial institutions that have gone bankrupt would not be included in the sample a bias would occur as only the strong institutions that survived are used.

The data is divided into subgroups using the Global Industry Classification Standard (GICS). GICS is used as it is a globally accepted methodology as an industry analysis framework. The industry groups within GICS are reviewed on a yearly basis to ensure the structure remains fully representative of today's global markets (GICS, 2016). According to GICS the financial sector is under divided into the following industries: banks, diversified financials, insurance and others. In similar research industries are divided into banks, broker dealers, insurance and others. I follow these researches and use broker dealers instead of diversified financials. The others industry is mainly dominated by real estate stocks. This research divides the data into these industries to differentiate between the levels of systemic risk in the different industries over time. It is to be expected that the industries with the highest risk will play the biggest role whenever a crisis occurs. In this part of the research it is even more important to ensure that there are sufficient data points available at each point in time to be able to say something about rarely occurring extremes at each point in time since the data samples used are smaller. At each point in time and considering all the different sectors there are always at least 11 extremes. Usually there are around 100 extremes that are used to define the Hill Alpha. I assume this is sufficient to get a reliable result.

In previous research when considering the data often only the largest financial institutions are taken. The reasoning for taking only the largest financial institutions is that it is believed that they have the biggest systemic impact. The most common argument is that these institutions are the most important because of the notion of "too big to fail". Even though it makes intuitive sense that large financial institutions are interconnected to a lot of other financial institutions and therefore are largely subject to systemic risk, a group of smaller institutions can also act as a systemic herd and create a systemic crisis throughout the sector. Therefore, I argue it is important to also include the smaller firms.

4 Empirical results

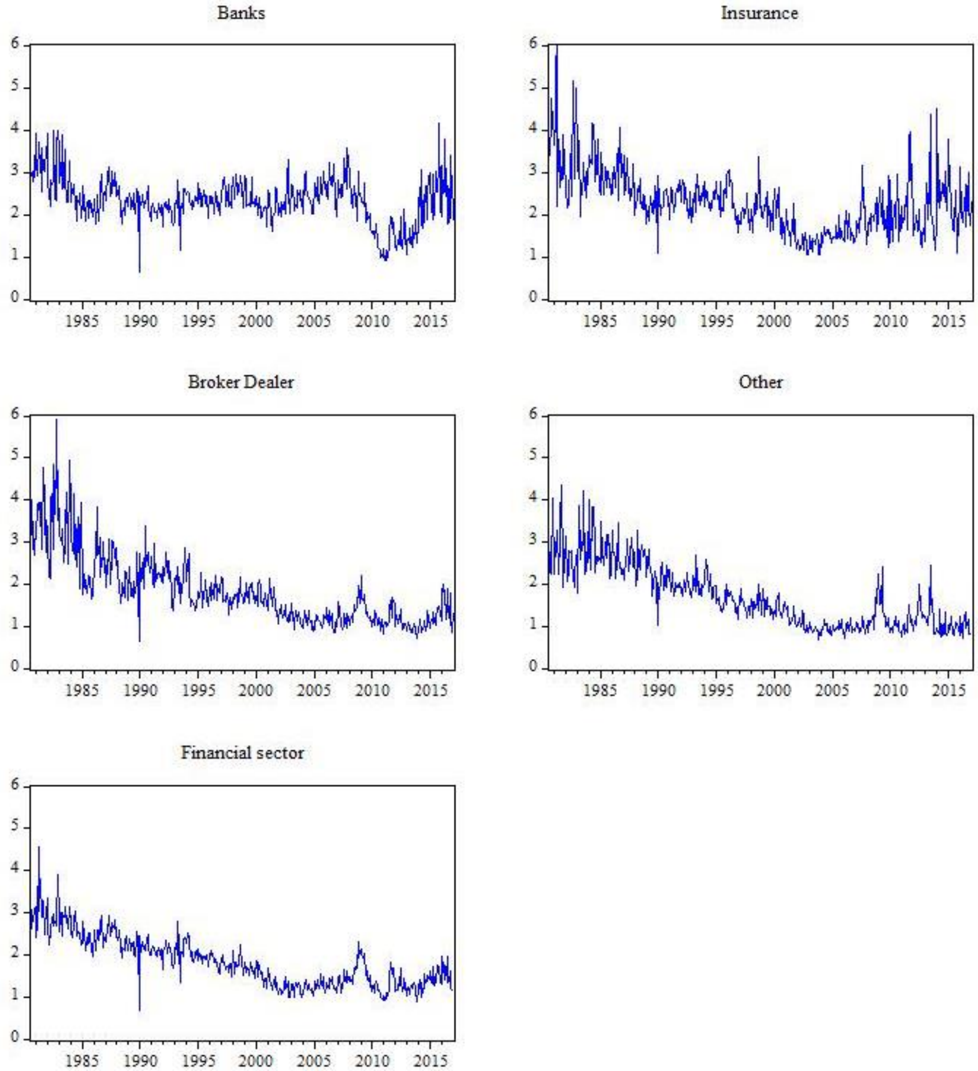
4.1 Time-varying tail risk estimates

Figure I reports the Hill estimator over a time line from 1980 to 2017 for the different industries and the sample of the entire financial sector. The figure is a panel with equal vertical scales to be able to better define the differences between the different industries and the financial sector. Every graph represents the Hill alpha for the defined sector or industry. To ensure that the visible variations are real a confidence interval is calculated following the formula in equation 3.1. Even considering a confidence interval of 95 percent there are clear variations in the Hill estimator over time for both the different industries and the financial sector. This confidence interval is not depicted in the panel graphs as it takes away from the clarity of the graphs.

(3.1) $\hat{\sigma}_{\hat{\alpha}} = \frac{\hat{\alpha}}{\sqrt{m}}$, with $Confidence\ interval = \hat{\alpha} \pm 1{,}96 \times \hat{\sigma}_{\hat{\alpha}}$

There are several conclusions that can be drawn from figure I. Firstly, the high Hill alpha in 1980 and 1981 can be seen as an indicator of the US recession of 1981-1982. Thereafter, leading up to the 1989-1991 US savings and loans crisis we can see the Hill alpha rising again for the banking industry and the broker dealer industry until approximately 1988. Surprisingly, the measure does not display a rise in systemic risk due to the arrival of the OTC derivatives market in 1995. Only the banks and broker dealer industries display a rise in systemic risk. This makes intuitive sense as those industries are related the most to the derivatives market. This rise in systemic risk can however be found in the time series of the DEHD estimator calculated for the financial sector, which is displayed in figure I in Appendix A.

Figure I Panel data – Hill estimator comparison



This figure includes graphs depicting the time-varying Hill estimator over a timeline from 1980-2017 for the financial sector and the different industries this sector contains. These industries include the banking, insurance, broker dealer and other industry. The Hill alpha is used as a proxy for systemic risk.

Then, there is a relatively stable period for all measures but the banking industry, until the dot com crash in 2001 after which the Hill alpha starts to decline. Only to start rising again leading up to the 2008-2011 global financial crisis. Moreover, leading up to the financial crisis in 2008 the banking industry displays a growing and relatively large Hill alpha and this industry seems to be the first to show signs of a financial downturn arising. This makes intuitive sense as banks played a major role in the financial crisis from 2008-2011. Nevertheless, taking into account the immense failures and defaults within the financial sector I expected to see a larger rise in systemic risk in all the industries as well as the financial sector leading up to the crisis. Interestingly, we can see that there has been an increase again in the Hill alpha from 2013 onwards and especially the banking industry displays a lot of variance. This could indicate that there is a small after crisis bound to arrive soon.

To ensure that the systemic risk measure is significantly different for the four different industries a t-test is performed. This test provides us with the result that the hypotheses that the different estimators are the same can be rejected at the 95% confidence interval. For the bank Hill estimator and the insurance Hill estimator, this hypothesis can only be rejected at the 90% confidence interval. For visualization purposes a frequency distribution is included in the appendix figure II. Similar to the findings of Billio et al. (2012) I find that the banking industry and secondly the insurance industry display the largest systemic risk over time.

Thus, it is to be expected that a shock in one of these industries will have the largest spillover impact within the industry. Which indicates that a shock in one of these industries is possibly also the most damaging to the entire market as their shocks are more severe. Especially in today's environment it is necessary to understand the importance of systemic risk. As the links between the industries within the financial sector are ever expanding and the impact of the financial sector and its industries in transmitting systemic risk to the real economy is substantial, since the financial sector is at the core of investments. Thus, my research indicates that the banking industry, closely followed by the insurance industry has the highest level of systemic risk and regulators should take close care of the level of systemic risk in these industries.

4.2 Predicting stock market returns

Moreover, the same regression as in Kelly and Jiang (2014) is performed on the CRSP value-weighted market index returns. This enables me to compare the usefulness of the Hill estimator using stocks of solely the financial sector versus using stocks of the entire market. Even more specifically I perform a regression on the CRSP value-weighted market index returns using the Hill estimator for the banking industry as the independent variable. In addition, I can compare these regressions to the regression on other predictive variables Kelly and Jiang (2014) performed in their paper. This enables me to study the usefulness of the time-varying tail risk measure of the financial sector versus the entire market and versus the other predictors of a financial crisis used in their paper.

For these regressions a timeline from 1980-2016 is used and the regressions are performed at a monthly frequency. Similar to Kelly and Jiang (2014), I test the predictive power over a time period of 1 month, 1 year, 3 years and 5 years. Since the data is performed at a monthly frequency there is an overlap in the data observations for the 1-year, 3-year and 5-year analysis and therefore the Hodrick's standard error for overlapping data is used. The independent variables in the regressions consist out of the estimated Hill alpha for the financial sector and the Hill alpha for the banking industry. They are used to measure the predictive power over the dependent variables, which consist out of the CRSP value-weighted market index returns over 1 month, 1 year, 3 years and 5 years. To be able to compare the obtained coefficient for the different timespans the returns of the CRSP value-weighted market index are annualized. The data is transformed in such a way that the coefficients can be interpreted as a one-standard-deviation increase in the predictive variable equals the coefficient's percentage change in future annualized returns.

Table I shows that over all horizons the Hill estimate for the financial sector has significant forecasting power. Notably, a one-standard deviation increase in the financial sector Hill estimator predicts a percentage increase in returns of 4.45%, 4.28%, 3.18% and 2.17% per annum for respectively a one-month, one-year, three-year and five-year horizon.

Table I
Market return predictability – predictive variable comparison

	One-month horizon			One-year horizon			Three-year horizon			Five-year horizon		
	Coeff.	t-stat.	R^2	Coeff.	t-stat.	R^2	Coeff.	t-stat.	R^2	Coeff.	t-stat.	R^2
Market Alpha*	4,54	2,08	0,70	4,02	2,04	6,10	3,65	2,40	16,60	3,16	3,16	20,90
Financial sector Alpha	4,45	1,23	0,53	4,28	2,06	7,02	3,81	4,03	15,12	2,17	2,71	8,40
Banking industry Alpha	0,44	-0,15	0,01	0,19	0,12	0,01	0,72	0,87	0,49	1,76	3,57	4,60
Book-to-market	4,08	0,94	0,45	3,22	1,25	4,05	3,06	2,95	10,25	2,31	2,74	10,71
Default return spread	1,97	0,89	0,10	0,33	0,61	0,04	-0,39	-1,03	0,15	-0,10	-0,41	0,02
Default yield spread	4,20	1,09	0,48	1,67	0,85	1,08	2,27	2,06	5,49	0,96	1,13	1,77
Dividend payout ratio	3,94	1,63	0,42	3,06	1,58	3,65	3,62	2,40	14,25	-0,33	-0,49	0,22
Dividend price ratio	6,05	1,71	0,99	5,26	2,22	10,80	4,16	3,55	18,72	2,80	3,27	15,53
Earnings price ratio	2,28	0,46	0,14	2,30	0,98	2,05	0,79	0,64	0,67	2,82	3,24	15,99
Inflation	-0,58	-0,20	0,01	1,30	1,24	0,65	0,94	1,12	0,88	1,16	2,65	2,33
Long-term return	5,16	1,87	0,72	-0,40	-0,62	0,06	0,19	0,49	0,04	0,00	0,00	0,00
Long-term yield	2,10	0,64	0,12	3,50	1,73	4,50	3,17	3,09	9,22	2,67	3,01	10,48
Net equity expansion	-1,30	0,04	0,05	1,52	0,64	0,85	0,41	0,25	0,17	-3,17	-2,82	17,75
Stock volatility	-3,11	-1,62	0,26	0,23	0,28	0,02	0,56	0,89	0,34	-0,22	-0,40	0,10
Term spread	1,21	0,44	0,04	2,91	0,91	3,30	-0,02	-0,02	0,00	-1,55	-1,57	4,77
T-bill rate	1,31	0,41	0,05	1,73	0,85	1,13	2,59	2,36	6,44	2,88	2,89	13,08

The table reports results from monthly predictive regressions of CRSP value-weighted market index returns over a one-month, one-year, three-year and five-year horizon. A period from 1980-2016 is used to calculate the results. The first three rows report the forecasting results based on the Hill estimator using the methodology proposed in this paper. The subsequent rows include the same predictors as are proposed in the survey by Goyal and Welch (2008), whilst using data from Amit Goyal's website. (*) denotes that the market Alpha variable has been calculated using a different period than the other variables as I do not possess the variable for a time period from 1980-2016. The results for this variable are taken from Kelly and Jiang who calculated the results using a timeline from 1963-2010. Since I use overlapping data Hodrick's standard error correction for overlapping data is used. For comparison purposes, the independent variables are transformed in such a way that the coefficients can be interpreted as a one-standard-deviation increase in the independent variable equals the coefficient's percentage change in future annualized returns.

The corresponding Hodrick t-statistics equal 1.23, 2.06, 4.03 and 2.71. The results from table I indicate that the financial sector Hill estimate has similar predictive power as the market Hill estimate as the Hodrick t-statistics for both are very similar. However, it should be noted that the market Hill estimate is calculated over a different time period, during which other predictive variables also displayed higher t-statistics as can be seen in table I from Kelly and Jiang (2014).

Table I also compares the predictive power for different variable, using the Hodrick t-statistic as a proxy for the usefulness of each variable. The larger the number of the t-statistic, either positive or negative, the greater the predictive power of the independent variable. It displays similar findings to Kelly and Jiang (2014) as only the dividend price ratio has comparable good results to the financial sector Hill estimate, when we exclude the market Hill estimate. Furthermore, over the short horizon of 1-month the dividend payout ratio, long-term return and stock volatility are similar in predictive power. However, over bigger time-horizons their predictive power dies out. On the other hand, the book-to-market ratio, long-term yield and the T-bill rate show similar predictive power to the financial sector Hill estimate over the long horizons of three and five year. Nonetheless, their predictive power is not as strong as the Hill estimate over a short horizon.

4.3 Predicting a recession in the real economy

To measure the usefulness of the Hill estimator several regressions are performed on different variables that are directly linked to a situation of a recession in the real economy. These variables consist out of the value weighted market index, GDP growth, the unemployment rate and industrial production. Importantly, these variables are directly related to the state of the real economy. All the regressions are conducted at a monthly frequency where possible. However, for GDP growth only yearly data is available and for the unemployment rate quarterly data and, therefore, I opt for these lower frequencies. Notably, my findings show that the Hill estimator has some predictive power over a future financial crisis. In table II my results are reported, and the different dependent variables are tested using the financial sector Hill alpha as a predictor. As table II shows, the financial sector Hill alpha has large predictive power over especially the value weighted market index and GDP growth as is shown by the high t-stat of around 3 for the one-year, three-year and five-year horizon. Considering the predictive power over the unemployment rate and industrial production the t-stat is a little lower but still shows that the Hill alpha contains predictive power.

Table II - Predictability of a recession in the real economy

	One-month horizon		One-year horizon		Three-year horizon		Five-year horizon	
	t-stat	R^2	t-stat	R^2	t-stat	R^2	t-stat	R^2
VW market index	1,23	0,53	2,06	7,02	4,03	15,12	2,71	8,40
GDP growth			3,31	25,49	2,32	15,17	2,73	21,04
Unemployment rate			3,91	9,83	1,20	1,08	-1,04	0,86
Industrial Production	1,27	0,36	0,97	0,22	2,90	2,02	3,21	2,63

The table reports results from monthly predictive regressions using a time period from 1980-2016. As the independent variable, the financial sector Hill estimator is used to predict the dependent variables. The dependent variables consist out of the VW market index (value weighted market index), GDP growth, the unemployment rate and industrial production. The data used is obtained from Bloomberg.

4.4 Generalized Extreme Value estimator

The DEDH estimator is calculated to evaluate whether the Hill alpha is rightfully used. For the DEDH estimator we look at gamma as calculated in equation 2.1. Over the whole time period, for both the full sample as well as the different industry groups, the DEDH estimator is positive. As $\hat{\gamma}$ is always positive I can conclude there is a high likelihood that the stocks in the financial sector have thus far been following a Pareto distribution. To check if gamma is always positive and greater than zero a t-test is performed for the financial sector as well as its industries. For the financial sector DEDH gamma the hypothesis that gamma is equal to zero can be rejected at the 99% confidence interval for all observed gammas from 1980 to 2017. As for the industries this hypothesis can be rejected at the 99% confidence interval for most observations of gamma and for all observations at the 95% confidence interval. This proofs that it is almost certain that over the timeline from 1980 to 2017 the stocks in the financial sector and its industries have been following a Pareto distribution and the Hill measure is rightfully used.

5 Discussion

This section provides a small discussion about the results obtained in section 4. Initially, figure I with the panel data is a visualization of the difference in the Hill estimate for the financial sector and the industries in the financial sector. Similar to Kelly and Jiang (2014) this figure I shows that there are time-variations in the Hill estimate and therefore it is useful to calculate the measure at each point in time. This figure also points out the increase of the systemic risk measure over time for the banking and insurance industry in comparison to the broker dealer and other industry. This rise in systemic risk for these two industries in comparison to the broker dealer and other industries is accentuated by figure II in appendix A. This figure shows that over the full time line from 1980 to 2017 these industries have the highest systemic risk on average. This indicates that they pose the highest risk on the real economy.

The regression depicted in table I shows that in comparison to the other predictors of future market returns, the financial sector Hill estimate performs at least as well as those other predictors. Also compared to the time-varying Hill estimate calculated for the entire market, as is done by Kelly and Jiang (2014), the financial sector Hill estimate is performing well. Taking the t-statistics as a proxy of performance for the predictors, the financial sector Hill estimate outperforms the market Hill estimate for the one-year and three-year horizon and underperforms for the one-month and five-year horizon. It is important to keep in mind that the market Hill estimate is not calculated within this paper and the regression results are taken from the paper of Kelly and Jiang (2014). Thus, a different timeline is taken for the market Hill estimate, which decreases the value of a comparison between the market Hill estimate and the financial sector Hill estimate calculated in this paper. Within the regression the banking industry is also calculated as I expected the banking industry Hill estimate to outperform the financial sector and market Hill estimates due to the large impact this industry has on the real economy. The banking industry has a large influence on the real economy as bank loans are at the basis of investments and thus of growth. However, the findings in table I show that the banking industry Hill estimate underperforms as a predictor for future market returns. One possible explanation could be that the banking sector Hill estimate could be dominated too much by smaller banks that do not have such a large systemic impact.

To analyze the predictive power of the financial sector Hill estimate on a financial crisis regressions are performed using the financial sector Hill estimate as the independent variable and the value weighted market index, GDP growth, unemployment rate and industrial production as the dependent variables. These variables are directly related to the state of the real economy. Especially for the value weighted market index and GDP growth a high t-stat and R^2 can be found, as is shown in table II, which indicates the financial sector Hill estimate is a useful predictor of a financial crisis. However, it is hard to decide on the predictive power of the financial sector Hill estimate as there are no other predictive variables used as a means of comparison.

6 Conclusion

The results in this paper indicate the industries in the financial sector contain different levels of systemic risk, with the banking industry and secondly the insurance industry exhibiting the highest systemic risk. Besides this, the research shows the usefulness of the Hill estimator from the financial sector as well as the banking sector to predict future market stock prices. Especially the financial sector hill estimate is a valuable predictor. Within this paper some regressions are also performed on indicators of a financial crisis using the financial sector Hill estimate as the independent variable. The regressions show that the financial sector Hill estimate has some value as a predictor of a future financial crisis.

Regarding future research a few expansions of this research can be considered. First of all, future research could expand the investigation of market return predictability by including a bivariate predictor performance as Kelly and Jiang (2014) perform in their paper. In a bivariate regression the financial sector Hill alpha together with one of the other predictive variables would be used as independent variables to predict the dependent variable of market return. In a further investigation research could also focus on the impact of regulatory changes or announcements made by the central bank on the Hill measure. It is to be expected that a response can be found in the Hill measure due to a noteworthy announcement of the Fed. Another suggestion for further research is to investigate both the US and Europe separately, as financial stability varies substantially between countries (Lehar, 2005). Thereafter, a comparison can be made between the Hill measures of both continents. In particular, it seems interesting to investigate the differences in the systemic risk measure in responses to a change of regulation by the central bank. Since the regulatory actions taken by the ECB versus the Fed differ substantially when looking at the financial crisis of 2008 (Loisel, 2007). One could expand even further by taking into account other parts of the world like Asia or emerging countries. Another extension of this research would be to use a more exact number of m to calculate a more precise Hill-estimator, to be able to work with a more accurate number of extremes. A more precise number of m can be found by looking at the Hill plot. Another way to determine m is to follow Goldie and Smith (1987) who proposed to select m in such a way as to minimize the asymptotic mean squared error (Straetmans et al., 2008).

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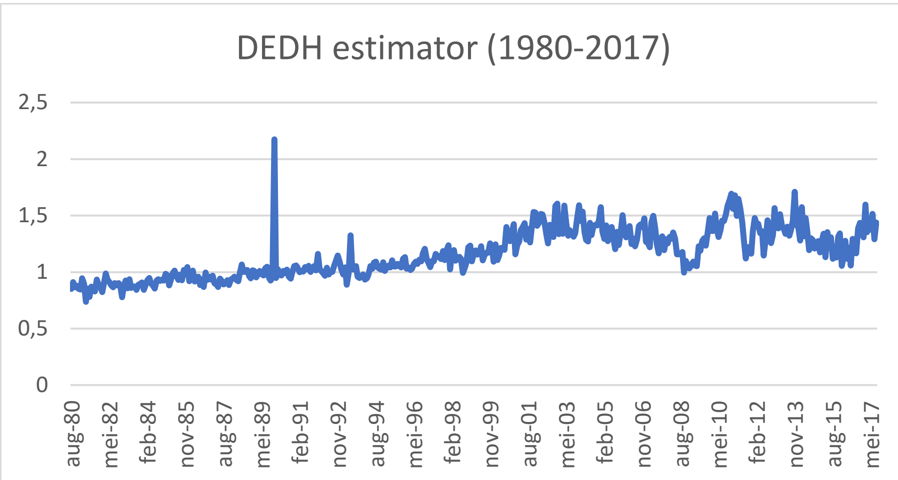
Appendix A

Figure I

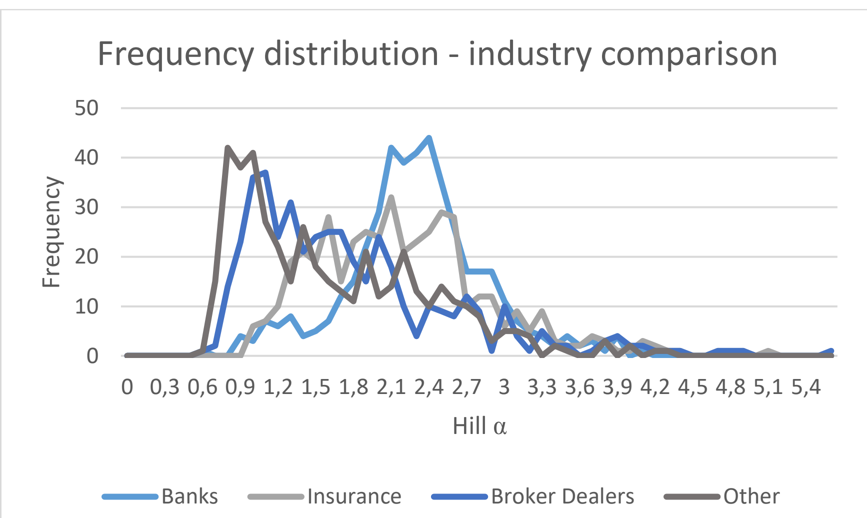
Financial sector DEDH estimator (1980-2017)



This figure displays the time-varying tail risk over a timeline from 1980-2017 using the general DEDH estimator for the financial sector data sample. In this graph the DEDH gamma is displayed. The observation that the DEDH estimator is always positive, indicates that the stocks in the financial sector thus far always followed a Pareto distribution.

Figure II

Frequency distribution – banking, insurance, broker-dealer and other industry



This figure displays the distribution of the Hill alpha using the observed frequency for a level of alpha between 0 and 5.6 to show the difference in the level of alpha between the 4 industries. It shows the difference in systemic risk between the industries.