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## Internet Searches, Household Sentiment and Credit Spreads

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Department of Economics  
School of Economics and Management

# Internet Searches, Household Sentiment and Credit Spreads

Hans Byström

October 2019



**LUND**  
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# Internet Searches, Household Sentiment and Credit Spreads

HANS BYSTRÖM<sup>\*</sup>

October 2019

We use Google internet search volumes to measure households' pessimism about overall market-wide credit health in the economy, and show that this "household default sentiment" is positively correlated with the credit default swap (CDS) spread level in the market. However, while household default sentiment might drive the cost of credit to some degree, either directly or indirectly through its effect on the stock market, we find the stock market's opinion about the credit risk in the economy (default probabilities backed out from structural models) to be much more important in explaining credit spreads. The rather weak link between household sentiment and CDS spreads, meanwhile, is consistent with the almost complete absence of retail investors (households) in the institutional investor-dominated credit derivatives market. The results are essentially the same, whether we look at market-wide CDS indexes or single-name CDS contracts, and whether we exclude the financial crisis or not.

Keywords: sentiment; Google; internet search; households; CDS; spread; distance to default

JEL classification codes: G12; G14; G50; D83; C82

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In this paper we shed some new light on the question of whether (household) sentiment affects credit spreads. We use a proxy for households' pessimism about overall credit health in the economy that was suggested by Irresberger et al. (2016) and show that "default sentiment" (i.e. "negative/pessimistic" credit-risk related sentiment) is correlated with the credit default swap (CDS) spread level in the market. Contrary to the somewhat surprising findings in Irresberger et al. (2016), however, we find the correlation to be positive. The correlation is not very strong, and though households' default sentiment might drive spreads in the credit derivatives market to some extent, either directly or indirectly via the stock market, we find Merton-style default probabilities backed out from ditto stock market, i.e. the stock market investors' collective opinion (default sentiment) about the credit risk in the economy, to be much more important in explaining CDS spreads. The rather weak link between household sentiment and credit derivatives prices is in line with expectations considering the almost complete absence of retail investors and households in the institutional investor-dominated credit derivatives market.

Numerous studies have tried to explain the variation in credit spreads. While some studies show that traditional macroeconomic- or firm-specific information explains a significant portion of the credit spread variation, other studies question the explanatory power of such variables. Ericsson et al. (2009) is one of the studies who find that firm-specific determinants of default risk, such as leverage, equity volatility and the risk-free interest rate explain much of the variation in CDS spreads. And Zhang et al. (2009), focusing on the effect of equity volatility and jumps on CDS spreads, finds that volatility risk alone explains around half of the credit spread variation. Collin-Dufresne et al. (2001), on the other hand, finds that credit spread changes in the corporate bond market instead is driven by local supply/demand shocks that are independent of changes in both default risk and liquidity. And Tang et al. (2013) finds that changes in firm fundamentals only

explain a fraction of the changes in CDS spreads. Instead, buy-sell trade imbalances (net buying interest in-between trades) are found to drive credit spreads.

As mentioned above, another possible driver of credit spreads is (investor) sentiment. Tang et al. (2010), for example, looks at the link between investor sentiment and credit spreads, measuring sentiment using the monthly Conference Board Consumer Confidence Index (CCI). They find (“positive/optimistic”) investor sentiment to be significantly and negatively related to credit spreads, and since investor sentiment is usually negatively correlated with market-wide risk aversion and uncertainty, this result is consistent with the notion that credit spreads depend on investors’ risk attitude and on their uncertainty about the future. In another study on sentiment, Lee et al. (2017) finds that changes in investor sentiment explains a significant portion of CDS spread changes, even when controlling for traditional structural variables, both on the firm-level and on a portfolio-level. Among the sentiment measures, Lee et al. (2017) finds the equity put/call ratio to explain the largest share of the credit spread changes. Sentiment seems to be particularly important in turmoil periods and for non-investment grade firms.

Building on the literature on investor sentiment, Irresberger et al. (2016) identifies household sentiment, rather than investor sentiment, as a previously neglected variable explaining credit spreads. Instead of employing traditional proxies for sentiment, such as survey responses, or market-based measures such as option implied volatilities or mutual fund flows, Irresberger et al. (2016) measures household sentiment using Google internet search volumes. This approach was pioneered by Da et al. (2011) who measures investor attention using Google searches. As argued by Da et al. (2011), Google search volumes have the twin advantages of both representing the internet search behavior of the general population and of being a revealed attention measure: if you search for something on Google, you are undoubtedly paying attention to it. Further, assuming that people who search for financial information on Google are more likely to be

individual/retail investors rather than institutional investors, Da et al. (2011) finds strong evidence that Google searches capture the attention of individual/retail investors. In a follow-up paper, Da et al. (2015) aggregates Google search volumes of “negative/pessimistic” internet search queries such as “bankruptcy”, “credit card debt” and “inflation” to construct an index labeled FEARS (Financial and Economic Attitudes Revealed by Search). Increases in the negative sentiment captured by the FEARS index are found to be negatively correlated to asset returns. The household default sentiment index suggested by Irresberger et al. (2016) also relies on Google internet search volumes, and in addition to being available on a monthly, or even weekly or daily, basis it has the advantage of being exogenous in the sense that it is not likely to be driven by the CDS market participants themselves. This gives us an indicator of default sentiment that is both frequently updated and that to a large extent is driven by households rather than credit derivatives investors.

While we build directly on the work by Irresberger et al. (2016) in this paper, we believe that we contribute to the literature in several ways. In our empirical study we look at monthly updated default sentiment based on default risk-related internet search volumes over the time-period April 2005 - April 2019. Compared to Irresberger et al. (2016), our time-period is much longer (14 years rather than 6 years) which allows us to use monthly- instead of weekly data. This advantage is particularly important when we control for one of the main traditional drivers of CDS spreads, the (Merton-model) default probability backed out from the stock market.<sup>1</sup> Moreover, in addition to the global financial crisis our time period also includes the eurozone debt crisis.<sup>2</sup> Also, compared to the single-name CDS spreads studied by Irresberger et al. (2016), we instead look at

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<sup>1</sup> The default probability is much easier to estimate on a monthly basis than on a weekly basis since equity volatility estimates are needed.

<sup>2</sup> Another difference is that our time period also includes the, nowadays, widespread use of smartphone-based mobile web search, a method of web search common, not the least, among households.

market-wide CDS index spreads (we look at single-name CDS spreads in a robustness section). As highlighted by Lee et al. (2017), regression analysis on the portfolio-level, for example using indexes, rather than on the firm-level, limits problems with idiosyncratic risk. In addition, while Irresberger et al. (2016) focuses on the default sentiment in the US, by collecting US-based Google search volumes, we look at the default sentiment globally, collecting world-wide search volumes and linking these to market-wide CDS spread levels. Finally, instead of controlling for each component in the Merton-framework (stock price, volatility, leverage, interest rate) one by one, we compute actual default probabilities (distance to default) and control for this default probability in the spread regressions. This has the advantage of capturing the true non-linear relationship between each component (stock price etc.) and the CDS spread rather than (wrongly) assuming that they are all linearly related to the cost of credit.

Our empirical results differ substantially from those of Irresberger et al. (2016). While they find a negative relationship between household default sentiment and CDS spreads, we find a very clear positive relationship. Irresberger et al. (2016) links their results to market liquidity and explain the rather surprising negative relationship by the presence of noise traders and increased liquidity in the CDS market. Our results, instead, are consistent with the hypothesis that shocks to household pessimism, expressed via an increase in households' default risk-related Google searches, reflect actual increases in the default risk in the economy and that it is a signal to which traders in the CDS market react, leading to widening spreads. Our results are robust to the removal of the financial crisis and to the replacement of market-wide CDS index spreads with single-name CDS spreads from around the world. In the end, though, whether the opposite results in our study and the Irresberger et al. (2016) study is due to the differences listed in the previous paragraph or to something else is left for future research to show.

The rest of the paper is organized as follows. Section I describes the data and the empirical setup, section II presents the empirical results and section III concludes the paper.

## **I. Data and Empirical Methodology**

We measure household default sentiment using the default sentiment index suggested by Irresberger et al. (2016). The index is based on Google internet search volumes and we compute it on a monthly basis over the time-period April 2005 - April 2019 using Google Trends. For a detailed background on the construction of the default sentiment index, and on the choice of search terms included, we refer to Irresberger et al. (2016). Basically, the authors create an index reflecting the default sentiment of households and creditors by selecting thirty Google search phrases (bigrams and trigrams) related to firm- or credit defaults. Examples of search phrases are “bankruptcy filing”, “loan default” and “credit card debt”. The default sentiment index is defined as the equally weighted average search volume of the thirty phrases as presented by Google Trends. Rather than providing the absolute number of searches, the search volume in Google Trends is set relative to all other Google searches over a certain period of time. By indexing the search volume in this way, one controls for possible time-dependency in the overall internet activity. In addition to this indexing, the search volume is also normalized to vary between 0 and 100, where the highest search volume across the particular time period is rescaled to 100.

Our aim in this paper is to study the link between market-wide default sentiment and market-wide credit spreads, and we therefore collect Google Trends search data from all possible geographic regions, i.e. world-wide (Irresberger et al. (2016) looks at US searches). As a proxy for the market-wide price of credit we choose the most widely traded CDS index available, the iTraxx Europe CDS index. While this index is limited to firms domiciled in Europe it references internationally focused firms with business activity all over the world and with a global investor



base. Moreover, the 125 credit default swaps included in the iTraxx Europe index are among the most liquid CDS contracts available, minimizing the CDS spreads' liquidity components. Lee et al. (2017) finds sentiment to be particularly important for non-investment grade firms and in addition to the mother index, iTraxx Europe, which references 125 investment grade firms, we therefore also study the two CDS indexes iTraxx HiVol and iTraxx Xover; the first index references the 30 firms with the widest CDS spreads in iTraxx Europe and the latter index references 25 European sub-investment grade non-financial firms. The maturity of the (Euro-denominated) CDS contracts in the indexes is five years, the most liquid maturity, and the CDS data is sampled on a monthly frequency over the time-period April 2005 - April 2019 (computed as the average daily spread across the calendar month).

Theory, as well as an abundance of empirical findings, dictates that a firm's credit spread is linked to its stock price movements, and in this paper we control for this driver of CDS spreads using the distance to default measure from Merton (1974). The distance to default is closely related to the default probability, and the market-wide distance to default is expected to increase if the likelihood of bankruptcies in the economy decreases. In this paper, monthly market-wide distance to default is computed from within-month average stock (index) prices and volatilities. The within-month volatilities are computed as sample standard deviations using the daily stock price observations over the actual calendar month.<sup>3</sup> The four stock market indexes that we use as different proxies for the market-wide stock market in the distance to default calculations are, respectively, one Europe-centered stock index (Euro Stoxx), two global stock indexes (FTSE All World and MSCI World), and one US-centered stock index (S&P 500). The leverage ratio needed to compute the market-wide distance to default is from the "Data" web page of Professor

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<sup>3</sup> The possibility of matching the default sentiment index sampling frequency/window (monthly) with the volatility computation frequency/window (monthly) is one huge advantage of using a monthly frequency in the analysis.

Aswath Damodaran at New York University (debt to capital, average across all industries = 35.8%) and a simplifying assumption that we make is that it stays constant over the chosen time-period. As a proxy for the risk-free interest rate (which is an input to the Merton model) we use the 3 month US Treasury bill rate. For a more detailed discussion on the estimation of default probabilities and distances to default using the Merton model we refer to the literature (Merton, 1974; Crosbie and Bohn, 2003). Except for the default sentiment index and the leverage ratio, all data is downloaded from Datastream.<sup>4</sup>

## II. Empirical Results

We follow the literature and study the relationship between CDS spreads and default sentiment using both level- and first-difference data. Instead of absolute differences, however, we look at percentage differences, i.e. returns.<sup>5</sup> In Table I we present descriptive statistics for our variables (levels and returns); the default sentiment index (DSI), the CDS index spreads (iTraxx) and the distance to default (DD). The upper panel is for the variables themselves (i.e. level data) and the lower panel is for percentage changes (i.e. return data). The distributional properties of the various variables are quite similar, with a positive mean, a similar relative range/variability and a slight positive skewness and some excess kurtosis (the only exception being the default sentiment with its slightly negative kurtosis). Phillips-Perron tests for stationarity indicate that all variables, with the possible exception of the sentiment index, are stationary already at the level. As for the return data, the variables show a bit more scattered behaviour but the deviations from normality, as indicated by the skewness and kurtosis, is quite similar. All the return variables are stationary.

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<sup>4</sup> A small number of missing observations or clearly erroneous data has been removed and/or replaced by zeroes or interpolated values.

<sup>5</sup> Lee et al. (2017) discusses the advantages of using percentage returns (logarithm differences) rather than absolute differences in time-series studies on credit risk.

In Table II we present simple pair-wise correlations between our three CDS index spreads and the default sentiment index. All correlations are positive, both at the level and for returns, but while the level correlations are all significant, the return correlations are not always statistically significant.<sup>6</sup> To some extent, the positive correlation between household pessimism (default sentiment) and the cost of credit over the fifteen-year period is also seen in Figure 1 where the two are plotted on a monthly frequency (for all three CDS indexes).

The next step is to turn to regressions. Since we know from both theory and numerous empirical studies that one of the main drivers of a firm's CDS spread is the stock market's opinion on the default probability of the firm, we include the market-wide Merton-style distance to default measure on the right-hand side as a control variable along the default sentiment index. All regressions are run using returns to remove any non-stationarity in our original (level) time-series. For each one of the three CDS indexes we perform four OLS regressions; one with only  $\Delta DSI$  (default sentiment) on the right-hand side, one with only  $\Delta DD$  (distance to default) on the right-hand side, one with both  $\Delta DSI$  and  $\Delta DD$  on the right-hand side and one final regression where we include  $\Delta DSI$  and residuals from a second regression, this time of  $\Delta DD$  on  $\Delta DSI$ , on the right-hand side. These residuals,  $\Delta DD_{resid}$ , represent the portion of the effect of the distance to default on the credit spread that is not indirectly explained/caused by the default sentiment. That is, we filter out the sentiment-caused component from the distance to default factor.

$$\Delta CDS_t = \alpha + \beta \cdot \Delta DSI_t + \varepsilon_t \quad (1)$$

$$\Delta CDS_t = \alpha + \gamma \cdot \Delta DD_t + \varepsilon_t \quad (2)$$

$$\Delta CDS_t = \alpha + \beta \cdot \Delta DSI_t + \gamma \cdot \Delta DD_t + \varepsilon_t \quad (3)$$

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<sup>6</sup> The correlations are essentially unchanged when we follow Irresberger et al. (2016) and winsorize the default sentiment data at the 5% level. We find no monthly seasonality in the default sentiment index.

$$\Delta CDS_t = \alpha + \beta \cdot \Delta DSI_t + \gamma \cdot \Delta DDresid_t + \varepsilon_t \quad (4)$$

We then repeat the entire exercise four times (a-d) with *DD* estimated using the four different market-wide stock index portfolios; Euro Stoxx, FTSE All World, MSCI World and S&P 500.

The regression results are found in Table IIIa-d and when default sentiment is the sole explanatory variable (column one) the regression-parameter  $\beta$  for default sentiment is always positive. The regression results support the correlation results in Table II and even though the relationship is not always statistically significant, it indicates a positive, albeit weak, relationship between households' default sentiment and CDS spreads. When distance to default is the only explanatory variable in the regressions (column two), the regression-parameter  $\gamma$  for distance to default is always both negative and highly significant, indicating a strong positive relationship between the Merton-model default probability and CDS spreads. The  $R^2$ - and  $F$ -values are also much higher in the regressions when the default sentiment is replaced by the distance to default. Moreover, it is clear that, among the four stock portfolio alternatives (a-d), the market-wide default probabilities estimated using the European stock portfolio, i.e. the Euro Stoxx index, is somewhat better at explaining the variability in the CDS index spreads. This is a reasonable result since the three iTraxx CDS indexes are all averages (portfolios) of European firms' CDS spreads. The market-wide distance to default for the American stock portfolio, i.e. the S&P 500 index, is in turn performing slightly worse than the two measures based on global stock portfolios and this is in line with expectations as well as a validation of the Merton-model as a relevant and accurate control variable. In column three (of Table III) we regress the CDS spreads on default sentiment jointly with distance to default, and now any of the previous explanatory power of the default sentiment factor disappears. While the regression-parameter  $\beta$  is still always positive it is never statistically significant. The default probability, though, is still highly positively and significantly

related to the CDS spread. In other words, when we control for variations in firms' distance to default, the default sentiment of households explains less of the variation in the firms' CDS spreads than before. However, it is still possible that household sentiment affects the spreads indirectly, via the default probability, and to test for this we include residuals from a regression of  $ADD$  on  $ADSI$  in our credit spread regressions (column four). Essentially, we filter out the sentiment-caused component from the distance to default factor and since both the default sentiment factor and the residual distance to default factor (in column four) are still significant, we interpret this as evidence that default probabilities might be influenced by household sentiment but that other factors are more important. The household default sentiment, meanwhile, might influence CDS spreads, but largely in an indirect way via its effect on the stock market.

As for the economic significance of our results, the average impact of a one-standard deviation change in household default sentiment on the iTraxx Europe CDS index spread is a little bit more than one seventh of a one-standard deviation change. Albeit not large, the impact is economically (somewhat) meaningful at twice the size of the mean iTraxx Europe CDS index spread change. For the distance to default, meanwhile, the effect is more significant; the average impact of a one-standard deviation change in distance to default on the iTraxx Europe CDS index spread is more than one third of a one-standard deviation change (five times the mean spread change). The economic impact of default sentiment on asset prices, in our case CDS spreads, is comparable to the economic impact on asset prices found in other studies. Da et al. (2015), for example, who aggregates Google search volumes of "negative" internet search queries just like us when they construct their FEARS sentiment index, finds that a one-standard deviation increase in negative sentiment corresponds to a contemporaneous decline of one tenth of a one-standard deviation

change in the S&P 500 index.<sup>7</sup> And Tang et al. (2013) shows that when the buy-sell trade imbalance (net buying interest) increases by one standard deviation, CDS spreads increase by three times the mean spread change.

For robustness, we replace our CDS indexes with single-name CDS contracts and study whether the effect of default sentiment on the spreads of these single-name CDS contracts is any different from that on the spreads of the CDS indexes. Here, we follow more closely in the footsteps of Irresberger et al. (2016), who looked solely at single-name CDS spreads. For comparative reasons we now also choose the exact same time period as Irresberger et al. (2016), i.e. January 2004 - September 2010. The underlying firms in our single-name CDS study are the fourteen firms with available CDS data in Datastream (see Table IV), among the 30 largest public firms in the world as listed by Forbes in 2019. Since the firms come from all over the world we choose to use the distance to default associated with the FTSE All World index as our control variable. As for the results of this robustness exercise, we still find the opposite results to Irresberger et al. (2016), i.e. once again we find a positive relationship between CDS spreads and household default sentiment. As for the single-name correlations in Table IV, they are similar to those for the CDS indexes and they are all positive both for levels and returns. The (pooled) regression results for the single-name CDS spreads in Table V are also similar to those for the index spreads. If anything, the positive link between household sentiment and this set of single-name CDS spreads is slightly stronger than for the iTraxx CDS indexes. The effect of the default sentiment on CDS spreads is now significant also when we control for the Merton (1974) default probability. The stand-alone explanatory power of the default sentiment is also more significant than in the case of the indexes.

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<sup>7</sup> This number is based on our calculations, assuming that a daily one-standard deviation change in S&P 500 over the time-period January 1, 2004 – December 31, 2008 is 1.3% (130bp).

The financial crisis in 2008-2009 had its epicenter in the credit (derivatives) market and it is possible that the heightened level of household pessimism regarding the credit health in the economy during this episode (see Figure 1) drives our results. Lee et al. (2017), for instance, finds sentiment to be particularly important in turmoil periods. As a second robustness test we therefore remove two years around the financial crisis (January 2008 - December 2009) and rerun the regressions for the market-wide CDS index spreads for the period 2005-2019. The results (in Table VI) show only minor changes in the regression parameters, and the link between (pessimistic) household default sentiment and credit spreads in the CDS market is, again, always positive.<sup>8</sup>

### **III. Conclusion**

Numerous studies have tried to explain the time-series variation in credit spreads. While some studies find factors such as macroeconomic- or firm-specific information to explain a significant portion of the credit spread variation, other studies have instead suggested investor sentiment as a possible explanatory variable for credit spreads. Irresberger et al. (2016) builds on this literature and identifies household sentiment, rather than investor sentiment, as a previously neglected variable explaining credit spreads. Instead of employing traditional proxies for sentiment, such as survey-based measures, Irresberger et al. (2016) measures household sentiment using Google internet search volumes.

In this paper we use the Irresberger et al. (2016) measure for households' pessimism about overall credit risk in the economy and show that this "household default sentiment" is correlated with the overall credit spread level in the market. Contrary to the surprising findings in

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<sup>8</sup> Opposite to Lee et al. (2017), we also do not find the sentiment to be more important for non-investment grade firms than for investment grade firms.

Irresberger et al. (2016), however, we find default sentiment (i.e. “negative” sentiment) to be positively, albeit weakly, correlated with CDS spreads, both for levels and returns. However, while household default sentiment, to some degree, might drive the cost of credit, either directly or indirectly through its effect on the stock market, we find the stock market’s opinion about the credit risk in the economy to be much more important in explaining credit spreads in the credit derivatives market. The rather weak link between household sentiment and the price of credit is in line with prior expectations, considering the lack of retail investors (households) in the institutional investor-dominated credit derivatives market. The results are essentially the same whether we look at market-wide CDS indexes or single-name CDS contracts, and the relationship between default sentiment and credit spreads is also found to be robust to the exclusion of the 2008-2009 financial crisis.



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**Table I**  
**Descriptive Statistics**

In this Table we present descriptive statistics for the default sentiment index (DSI), the credit default swap index spread (iTraxx) and the distance to default (DD). The time period is April 2005 - April 2019, i.e. 168 months, and we present statistics both for levels and changes (returns). All returns are in percent and the CDS spreads are in basis points. All time-series are sampled on a monthly frequency. *Skew* is skewness, *Kurt* is excess kurtosis and *PP* is the Phillips-Perron Test with 4 Lags with/without a trend.

	DSI	iTraxx Europe	iTraxx HiVol	iTraxx Xover	DD Euro Stoxx	DD FTSE All World	DD MSCIWorld	DD S&P 500
<b>Levels</b>								
<i>Mean</i>	24.0	82.9	116.7	403.9	12.2	18.5	18.0	16.2
<i>Std. Dev.</i>	9.0	40.1	85.8	179.3	5.7	9.6	9.5	8.6
<i>Max</i>	46.7	189.9	486.9	1066.3	30.5	60.4	61.9	42.9
<i>Min</i>	12.1	21.8	35.2	185.2	1.9	2.1	2.0	1.6
<i>Skew</i>	0.7	0.8	1.4	1.6	0.7	1.0	1.1	0.8
<i>Kurt</i>	-0.6	0.2	2.4	2.5	0.3	1.7	2.1	0.3
<i>PP (trend)</i>	-4.4	-9.6	-9.2	-10.1	-52.1	-52.9	-57.0	-65.4
<i>PP</i>	-17.3	-9.4	-10.9	-11.2	-53.5	-63.9	-67.7	-80.9
<b>Returns</b>								
<i>Mean</i>	0.11	1.05	0.38	0.49	7.73	9.52	9.90	11.7
<i>Std. Dev.</i>	10.6	13.6	13.6	11.3	40.4	46.1	47.4	52.4
<i>Max</i>	34.3	56.9	52.5	50.6	144.7	221.1	227.3	267.1
<i>Min</i>	-42.1	-32.3	-34.9	-21.6	-63.5	-66.8	-67.8	-75.8
<i>Skew</i>	0.4	1.5	1.2	1.6	0.77	1.2	1.3	1.4
<i>Kurt</i>	1.9	3.8	2.4	3.9	0.75	2.6	2.9	3.2
<i>PP (trend)</i>	-193.2	-127.8	-112.2	-136.5	-182.5	-188.0	-189.1	-185.5
<i>PP</i>	-193.3	-127.9	-112.7	-136.6	-182.4	-187.3	-188.1	-184.5

**Table II**  
**Correlations - default sentiment and CDS index spreads**

In this Table we present Pearson correlation coefficients between the default sentiment index (DSI) and credit default swap index spread levels and changes (returns). The time period is April 2005 - April 2019 and the correlations are for monthly data, i.e. for monthly DSI observations and for monthly CDS index spreads. \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively.

	iTraxx Europe	iTraxx HiVol	iTraxx Xover
		<b>Levels</b>	
<b>DSI</b>	0.17**	0.48***	0.51***
		<b>Returns</b>	
<b>DSI</b>	0.15*	0.15*	0.12

Table IIIa

**OLS Regressions – changes in default sentiment and CDS index spreads**

In this Table we present regression results for three European credit default swap indexes. The credit default swap index spread change is always the dependent variable and the independent variables,  $\Delta DSI$ ,  $\Delta DD$  and  $\Delta DDresid$ , are changes in the default sentiment and changes in the distance to default and its residuals for the average firm in the Euro Stoxx index, respectively. The small numbers in brackets are  $p$ -values and \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively. The regressions are based on 168 monthly observations from April 2005 to April 2019. The three panels are identical except for the dependent variable, which is, respectively, iTraxx Europe, iTraxx HiVol and iTraxx Xover. iTraxx Europe is the credit spread of a typical European investment grade firm, iTraxx HiVol is the credit spread of a more risky European investment grade firm, and iTraxx Xover is the credit spread of a typical European sub-investment grade firm.

<b>iTraxx Europe</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.187* (0.059)		0.047 (0.622)	0.187** (0.043)
$\Delta DD$		-0.132*** (0.000)	-0.129*** (0.000)	
$\Delta DDresid$				-0.129*** (0.000)
<i>Intercept</i>	0.010 (0.326)	0.021** (0.037)	0.020** (0.041)	0.010 (0.292)
$R^2$	0.021	0.154	0.156	0.156
$\hat{R}^2$	0.015	0.149	0.145	0.145
$F$	3.62* (0.059)	30.32*** (0.000)	15.21*** (0.000)	15.21*** (0.000)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx HiVol</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.194* (0.051)		0.088 (0.375)	0.194** (0.043)
$\Delta DD$		-0.104*** (0.000)	-0.097*** (0.000)	
$\Delta DDresid$				-0.097*** (0.000)
<i>Intercept</i>	0.004 (0.732)	0.012 (0.248)	0.011 (0.275)	0.004 (0.722)
$R^2$	0.023	0.095	0.099	0.099
$\hat{R}^2$	0.017	0.089	0.088	0.088
$F$	3.87* (0.051)	17.39*** (0.000)	9.08*** (0.000)	9.08*** (0.000)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx Xover</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.131 (0.112)		0.021 (0.790)	0.131* (0.091)
$\Delta DD$		-0.102*** (0.000)	-0.101*** (0.000)	
$\Delta DDresid$				-0.101*** (0.000)
<i>Intercept</i>	0.005 (0.581)	0.013 (0.122)	0.013 (0.129)	0.005 (0.557)
$R^2$	0.015	0.134	0.134	0.134
$\hat{R}^2$	0.009	0.129	0.124	0.124
$F$	2.55 (0.112)	25.65*** (0.000)	12.79*** (0.000)	12.79*** (0.000)
<i>No. Obs.</i>	168	168	168	168

Table IIIb

**OLS Regressions – changes in default sentiment and CDS index spreads**

In this Table we present regression results for three European credit default swap indexes. The credit default swap index spread change is always the dependent variable and the independent variables,  $\Delta DSI$ ,  $\Delta DD$  and  $\Delta DDresid$ , are changes in the default sentiment and changes in the distance to default and its residuals for the average firm in the FTSE All World index, respectively. The small numbers in brackets are  $p$ -values and \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively. The regressions are based on 168 monthly observations from April 2005 to April 2019. The three panels are identical except for the dependent variable, which is, respectively, iTraxx Europe, iTraxx HiVol and iTraxx Xover. iTraxx Europe is the credit spread of a typical European investment grade firm, iTraxx HiVol is the credit spread of a more risky European investment grade firm, and iTraxx Xover is the credit spread of a typical European sub-investment grade firm.

<b>iTraxx Europe</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.187* (0.059)		0.086 (0.375)	0.187** (0.047)
$\Delta DD$		-0.100*** (0.000)	-0.095*** (0.000)	
$\Delta DDresid$				-0.095*** (0.000)
<i>Intercept</i>	0.010 (0.326)	0.020** (0.050)	0.019* (0.057)	0.010 (0.302)
$R^2$	0.021	0.115	0.119	0.119
$\hat{R}^2$	0.015	0.109	0.108	0.108
$F$	3.62* (0.059)	21.47*** (0.000)	11.12*** (0.000)	11.12*** (0.000)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx HiVol</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.194* (0.051)		0.118 (0.237)	0.194** (0.045)
$\Delta DD$		-0.078*** (0.001)	-0.071*** (0.002)	
$\Delta DDresid$				-0.071*** (0.002)
<i>Intercept</i>	0.004 (0.732)	0.011 (0.281)	0.010 (0.315)	0.004 (0.726)
$R^2$	0.023	0.070	0.078	0.078
$\hat{R}^2$	0.017	0.064	0.067	0.067
$F$	3.87* (0.051)	12.46*** (0.000)	6.95*** (0.000)	6.95*** (0.000)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx Xover</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.131 (0.112)		0.050 (0.535)	0.131* (0.097)
$\Delta DD$		-0.078*** (0.000)	-0.075*** (0.000)	
$\Delta DDresid$				-0.075*** (0.000)
<i>Intercept</i>	0.005 (0.581)	0.012 (0.144)	0.012 (0.156)	0.005 (0.564)
$R^2$	0.015	0.102	0.105	0.105
$\hat{R}^2$	0.009	0.097	0.094	0.094
$F$	2.55 (0.112)	18.95*** (0.000)	9.63*** (0.000)	9.63*** (0.000)
<i>No. Obs.</i>	168	168	168	168

Table IIIc

**OLS Regressions – changes in default sentiment and CDS index spreads**

In this Table we present regression results for three European credit default swap indexes. The credit default swap index spread change is always the dependent variable and the independent variables,  $\Delta DSI$ ,  $\Delta DD$  and  $\Delta DDresid$ , are changes in the default sentiment and changes in the distance to default and its residuals for the average firm in the MSCI World index, respectively. The small numbers in brackets are  $p$ -values and \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively. The regressions are based on 168 monthly observations from April 2005 to April 2019. The three panels are identical except for the dependent variable, which is, respectively, iTraxx Europe, iTraxx HiVol and iTraxx Xover. iTraxx Europe is the credit spread of a typical European investment grade firm, iTraxx HiVol is the credit spread of a more risky European investment grade firm, and iTraxx Xover is the credit spread of a typical European sub-investment grade firm.

<b>iTraxx Europe</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.187* (0.059)		0.093 (0.340)	0.187** (0.048)
$\Delta DD$		-0.094*** (0.000)	-0.089*** (0.000)	
$\Delta DDresid$				-0.089*** (0.000)
<i>Intercept</i>	0.010 (0.326)	0.020** (0.053)	0.019* (0.061)	0.010 (0.303)
$R^2$	0.021	0.108	0.113	0.113
$\hat{R}^2$	0.015	0.103	0.102	0.102
$F$	3.62* (0.059)	20.15*** (0.000)	10.53*** (0.000)	10.53*** (0.000)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx HiVol</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.194* (0.051)		0.123 (0.218)	0.194** (0.045)
$\Delta DD$		-0.074*** (0.001)	-0.067*** (0.003)	
$\Delta DDresid$				-0.067*** (0.003)
<i>Intercept</i>	0.004 (0.732)	0.011 (0.288)	0.010 (0.323)	0.004 (0.726)
$R^2$	0.023	0.066	0.075	0.075
$\hat{R}^2$	0.017	0.061	0.064	0.064
$F$	3.87* (0.051)	11.76*** (0.000)	6.67*** (0.003)	6.67*** (0.003)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx Xover</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.131 (0.112)		0.056 (0.493)	0.131* (0.098)
$\Delta DD$		-0.074*** (0.000)	-0.071*** (0.000)	
$\Delta DDresid$				-0.071*** (0.000)
<i>Intercept</i>	0.005 (0.581)	0.012 (0.150)	0.012 (0.164)	0.005 (0.565)
$R^2$	0.015	0.097	0.099	0.099
$\hat{R}^2$	0.009	0.091	0.088	0.088
$F$	2.55 (0.112)	17.80*** (0.000)	9.11*** (0.000)	9.11*** (0.000)
<i>No. Obs.</i>	168	168	168	168

Table III

**OLS Regressions – changes in default sentiment and CDS index spreads**

In this Table we present regression results for three European credit default swap indexes. The credit default swap index spread change is always the dependent variable and the independent variables,  $\Delta DSI$ ,  $\Delta DD$  and  $\Delta DDresid$ , are changes in the default sentiment and changes in the distance to default and its residuals for the average firm in the S&P 500 index, respectively. The small numbers in brackets are  $p$ -values and \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively. The regressions are based on 168 monthly observations from April 2005 to April 2019. The three panels are identical except for the dependent variable, which is, respectively, iTraxx Europe, iTraxx HiVol and iTraxx Xover. iTraxx Europe is the credit spread of a typical European investment grade firm, iTraxx HiVol is the credit spread of a more risky European investment grade firm, and iTraxx Xover is the credit spread of a typical European sub-investment grade firm.

<b>iTraxx Europe</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.187* (0.059)		0.109 (0.260)	0.187** (0.048)
$\Delta DD$		-0.083*** (0.000)	-0.079*** (0.000)	
$\Delta DDresid$				-0.079*** (0.000)
<i>Intercept</i>	0.010 (0.326)	0.020** (0.049)	0.020* (0.056)	0.010 (0.304)
$R^2$	0.021	0.104	0.111	0.111
$\hat{R}^2$	0.015	0.098	0.100	0.100
$F$	3.62* (0.059)	19.24*** (0.000)	10.27*** (0.000)	10.27*** (0.000)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx HiVol</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.194* (0.051)		0.135 (0.173)	0.194** (0.046)
$\Delta DD$		-0.065*** (0.001)	-0.060*** (0.003)	
$\Delta DDresid$				-0.060*** (0.003)
<i>Intercept</i>	0.004 (0.732)	0.011 (0.276)	0.011 (0.310)	0.004 (0.726)
$R^2$	0.023	0.063	0.073	0.073
$\hat{R}^2$	0.017	0.057	0.062	0.062
$F$	3.87* (0.051)	11.14*** (0.000)	6.54*** (0.003)	6.54*** (0.003)
<i>No. Obs.</i>	168	168	168	168
<b>iTraxx Xover</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.131 (0.112)		0.071 (0.379)	0.131* (0.099)
$\Delta DD$		-0.063*** (0.000)	-0.060*** (0.000)	
$\Delta DDresid$				-0.060*** (0.000)
<i>Intercept</i>	0.005 (0.581)	0.012 (0.152)	0.012 (0.167)	0.005 (0.567)
$R^2$	0.015	0.086	0.090	0.090
$\hat{R}^2$	0.009	0.080	0.079	0.079
$F$	2.55 (0.112)	15.53*** (0.000)	8.15*** (0.003)	8.15*** (0.003)
<i>No. Obs.</i>	168	168	168	168

**Table IV****Robustness: Correlations - default sentiment and single-name CDS spreads**

In this Table we present Pearson correlation coefficients between the default sentiment index (DSI) and single-name credit default swap spread levels and returns. The time period is the same as that in Irresberger et al. (2016), i.e. January 2004 - September 2010 and the companies are the fourteen firms with CDS data in Datastream among the 30 largest public firms in the world as listed by Forbes in 2019. All the correlations are for monthly data, i.e. for monthly DSI observations and for monthly CDS spreads.

	JP Morgan	Wells Fargo	Bank of China	Royal Dutch Shell	Toyota	Exxon Mobil	Samsung	AT&T	VW	BNP Paribas	Chevron	Allianz	Total	United Health
<hr/>														
	<b>Levels</b>													
<b>DSI</b>	0.49	0.50	0.52	0.45	0.51	0.51	0.62	0.31	0.63	0.31	0.56	0.49	0.44	0.51
	<b>Returns</b>													
<b>DSI</b>	0.12	0.11	0.10	0.09	0.06	0.10	0.13	0.15	0.12	0.10	0.14	0.06	0.06	0.08



**Table V****Robustness: OLS Regressions – default sentiment and single-name CDS spreads**

In this Table we present pooled regression results for single-name CDS spread changes for the fourteen firms with CDS data in Datastream among the 30 largest public firms in the world as listed by Forbes in 2019. The small numbers in brackets are  $p$ -values and \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively. The time period is the same as that in Irresberger et al. (2016), i.e. January 2004 - September 2010, and the pooled regression is based on monthly data.

	(1)	(2)	(3)	(4)
$\Delta DSI$	0.181*** (0.001)		0.088* (0.098)	0.181*** (0.001)
$\Delta DD$		-0.158*** (0.000)	-0.152*** (0.000)	
$\Delta DD_{resid}$				-0.152*** (0.000)
<i>Intercept</i>	0.039*** (0.000)	0.050*** (0.000)	0.050*** (0.000)	0.039*** (0.000)
$R^2$	0.010	0.070	0.072	0.072
$\hat{R}^2$	0.009	0.069	0.070	0.070
$F$	11.24***	83.80***	43.34***	43.34***
<i>No. Obs.</i>	1120	1120	1120	1120

**Table VI**  
**Robustness: OLS Regressions – default sentiment and CDS index spreads excluding the crisis**

In this Table we present regression results for three European credit default swap indexes when the crisis years 2008 and 2009 are removed. The credit default swap index spread change is always the dependent variable and the independent variables,  $\Delta DSI$ ,  $\Delta DD$  and  $\Delta DDresid$ , are changes in the default sentiment and changes in the distance to default and its residuals for the average firm in the Euro Stoxx index, respectively. The small numbers in brackets are  $p$ -values and \*, \*\* and \*\*\* represent significance at the 10%, 5% and 1% level, respectively. The regressions are based on 144 monthly observations from April 2005 to April 2019, excluding January 2008 to December 2009. The three panels are identical except for the dependent variable, which is, respectively, iTraxx Europe, iTraxx HiVol and iTraxx Xover.

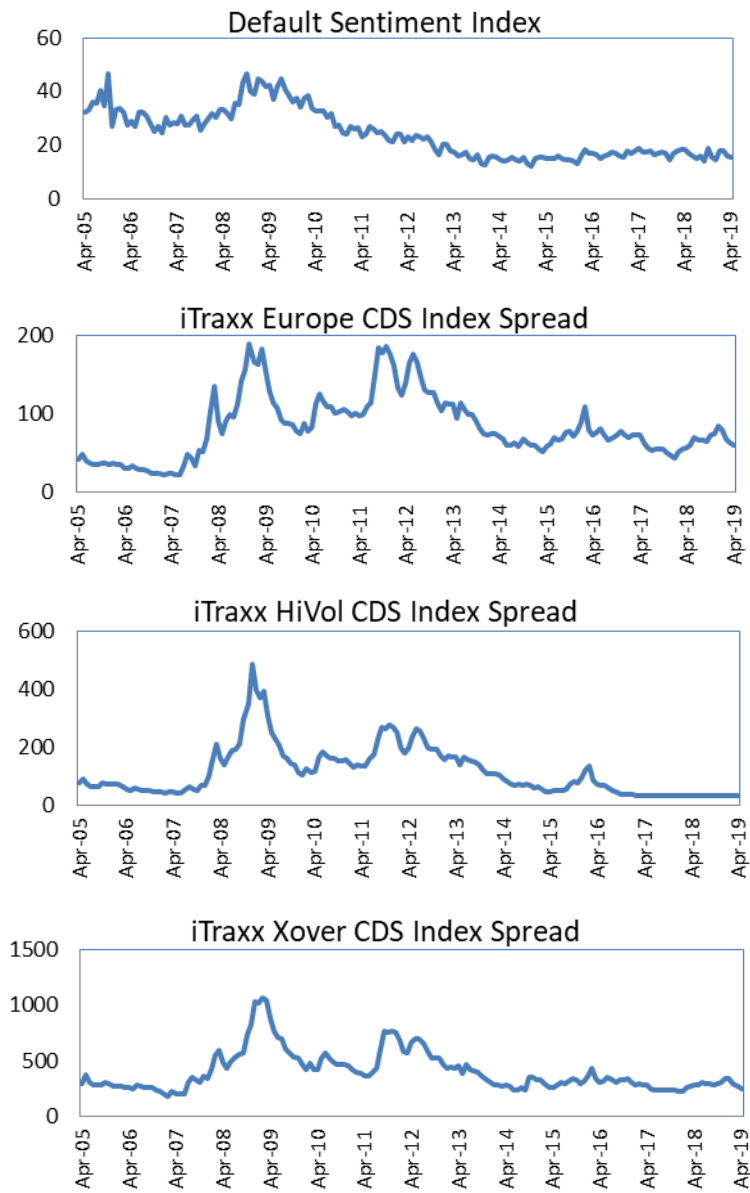
<b>iTraxx Europe</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.170* (0.074)		0.053 (0.560)	0.170* (0.054)
$\Delta DD$		-0.125*** (0.000)	-0.121*** (0.000)	
$\Delta DDresid$				-0.121*** (0.000)
Intercept	0.006 (0.526)	0.016* (0.098)	0.016 (0.105)	0.006 (0.493)
$R^2$	0.022	0.166	0.168	0.168
$\hat{R}^2$	0.015	0.160	0.157	0.157
$F$	3.23*	28.33***	14.27***	14.27***
No. Obs.	144	144	144	144

<b>iTraxx HiVol</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.167* (0.056)		0.082 (0.343)	0.167** (0.046)
$\Delta DD$		-0.093*** (0.000)	-0.088*** (0.000)	
$\Delta DDresid$				-0.088*** (0.000)
Intercept	-0.003 (0.766)	0.004 (0.634)	0.004 (0.667)	-0.003 (0.756)
$R^2$	0.025	0.111	0.117	0.117
$\hat{R}^2$	0.019	0.105	0.104	0.104
$F$	3.67*	17.79***	9.34***	9.34***
No. Obs.	144	144	144	144

<b>iTraxx Xover</b>				
	(1)	(2)	(3)	(4)
$\Delta DSI$	0.118 (0.163)		0.018 (0.826)	0.118 (0.135)
$\Delta DD$		-0.104*** (0.000)	-0.103*** (0.000)	
$\Delta DDresid$				-0.103*** (0.000)
Intercept	0.002 (0.808)	0.010 (0.237)	0.010 (0.243)	0.002 (0.794)
$R^2$	0.014	0.149	0.150	0.150
$\hat{R}^2$	0.007	0.143	0.138	0.138
$F$	1.96	24.92***	12.40***	12.40***
No. Obs.	144	144	144	144



**Figure 1. Default Sentiment and Credit Default Swap Index Spreads.** This graph shows the monthly default sentiment index (DSI) together with the three monthly iTraxx CDS index spreads (bp) over the time-period April 2005 – April 2019.