

Time Series Variation in Corporate Credit Rating Standards from 1986 to 2017

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Abstract

The average rating of US Corporate debt has trended downward since the mid-80s. Existing research [Blume et al (1998), Baghai et al (2014)] argues that this trend was caused by an increase in conservatism on the part of rating agencies. When holding firm characteristics constant, ratings appear to deteriorate from the period between 1985 and 2007. I build on the work done previously, while extending the range of data out through 2017 to see if the trend of increased conservatism has continued and find that the trend has leveled off from 2007-2017. I analyze investment grade versus sub-investment grade and find the effect most pronounced in the investment grade space. Finally, I look at sector specific impacts and find that while all sectors were impacted, the Communications sector experiences the largest increase of conservatism.

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1. Introduction

Standard and Poor's defines a credit rating as 'an educated opinion about an issuer's likelihood to meet its financial obligations in full and on time (Standard and Poor's, 2019). Over recent decades there has been an observable decline in the average rating of US corporate debt, the question is why?

A few broad possible explanations exist: a) the inherent credit quality of US issuers has been declining, thus fewer meet S&P's standard of capacity and willingness to meet their financial obligations, b) the characteristics of US issuers has not changed, but rather the standards by which S&P generates its ratings have become more stringent, or c) a combination of both. In this paper, I examine option 'b'- whether the standards used by S&P have been increasing over time. If true, the implications are significant, as Jorion et al. (2008) put it, '..a tightening of credit standards by rating agencies, if it occurred, could undermine the usefulness of credit ratings and have an adverse impact on the cost of debt financing.'

I run a series of OLS regressions which control for firm characteristics to see if there is in fact an increase in the standards of S&P ratings. I regress credit ratings against a variety of factors ('Debt/EBITDA', 'Cash/Assets', 'Firm Size', 'Debt/Assets', etc) obtained from published quarterly financial reports, as well as an Indicator Variable for each year. This Indicator Variable is generated by assigning a Dummy Variable of 1 or 0 to each year in the sample. The Dummy Variables seek to capture any annual effects not picked up by the firm characteristics. If there is no change in level of conservatism of credit rating methodologies, the coefficient of these Dummy Variables should remain constant. However, I find that the Dummy Variable coefficients trend upward over time suggesting that S&P has become more conservative over time.

A good deal of research has been done on this subject: Blume et al. (1998), Jorion et al (2008), Alp (2013), and Baghai et al. (2014). In each case the authors control for firm-specific characteristics (using a variety of financial accounting metrics) to see if in fact a time-varying effect does exist, and they find that this trend of increasing conservatism does exist.

I take a similar approach to that of Baghai et al (2014), however I extend the time series out from 2007 to 2017. I find that the trend of conservatism peaks around 2007 and remains stable through 2017. I also build on the work of Jorion et al. (2008) who (using data from 1981-2003) find a difference in the effect between Investment Grade and Speculative Grade[1] names. They find that the effect of

[1] S&P defines 'Investment Grade' as having a rating of 'BBB-' or better and 'Speculative Grade' refers to a rating of 'BB+' or worse.

increasing conservatism is only present with Investment Grade firms, not those rated as Speculative Grade.

Finally, I look to see if the effect of increased conservatism applies to all industries or only specific sectors. I add specific controls for Sector in addition to the base-case accounting metrics. I conclude that no specific sector was excluded from the increase in conservatism and the split between Investment Grade and Speculative Grade exists across all sectors.

2. Literature Review

In the following section I first provide a brief overview of credit rating agencies in terms of the benefit they provide to markets, the impact their announcements can have on markets, and some of the criticisms levied on these agencies. I then provide a recap of the papers which have led to this study of time-varying levels of conservatism observed in the behavior of credit rating agencies.

2.1 Background on Credit Rating Agencies

2.1.1 History and Purpose

Lawrence White's 2010 paper provides an overview of the history of rating agencies. John Moody published the first guide to bond ratings in 1909, which focused exclusively on railroad bonds. Later, in 1916 Poor's Publishing Company produced their own bond rating guide, followed by the Standard Statistics Company in 1922 and the Fitch Publishing Company in 1924. Poor's Publishing and the Standard Statistics Company merged in 1941 to form Standard and Poor's; which was later purchased by McGraw Hill in 1966 (White, 2010).

As White puts it, the purpose of credit rating agencies is to help pierce the fog of asymmetric information by offering judgments about the credit quality of a variety of bonds (White, 2010). Following the great stock market crash of 1929, regulators started imposing stricter guidelines on the kind of investments banks could hold. In 1936, a key piece of regulation was passed, which prohibited banks from investing in 'speculative investment securities' as determined by the 'recognized rating manuals' (White, 2010). This helped to create the dominant market positions held by Fitch, Moody's, Standard Statistics and Poor's Publishing; which still exists today.

While in theory, the act of bridging the gap of asymmetric information should be of value to efficient credit markets, there is some debate as to empirical benefits provided by rating agencies. Rating agencies like to point out that for each worse rating band there has been an increased level of defaults over time. However, one could argue that this same correlation could be observed by ranking bonds by their

market-determined credit spread over US treasuries. In this case, it is not clear what added value rating agencies provided above and beyond what is priced in by the market (White, 2010). The exception to this might be for new issuers or complex, structured products, for which transparent information is not easily accessible to market participants -securitized sub-prime loans would also fall into this category.

2.1.2 Market Impact of Credit Rating Announcements

There has been a great deal of research done on the impact of ratings announcements on bond and stock prices. One of the most frequently cited studies by Hand, Holthausen and Leftwich (Hand, 92) looks at the response of excess daily bond returns to announcements of rating agencies. The study finds that statistically significant average excess bond returns follow downgrades, with less reliable results in response to upgrades. Furthermore, they find that the downgrade impact is stronger on sub-Investment Grade (SIG) bonds compared to Investment Grade (IG) bonds. IG bonds had a mean excess return of -0.55% following a downgrade while SIG bonds saw a mean excess return of -3.82%.

In 2000, Kliger and Sarig publish another widely cited paper which focuses on the day to day change in bond prices following the change in the granularity of Moody's rating categories. On April 26th, 1982, Moody's increased the overall number of rating categories, thus adding more refinement to their rating bands. The benefit of focusing on this particular date is that a) it came as a surprise to the market and b) did not reflect any economic shock or to any particular firm. The results once again demonstrate a clear impact on bond prices- a decline in price following a negative downgrade and vice versa. They also note that following a surprise upgrade in rating, the implied volatility in options on that firm's traded shares also decline. Both studies illustrate that rating agencies can have a significant market impact- which in turn impacts the cost of debt issuance.

2.1.3 Criticisms of Rating Agencies

Another key turning point in the history of rating agencies came in the early 1970s when rating agencies began to change their business model from 'Investor Pays' to 'Issuer Pays'. The exact reasons for this shift are not knows, however, one theory suggests that with the advent of the photocopier, rating agencies feared that investors would be able to avoid paying for rating guides as they could simply photocopy these reports from a third-party. Nevertheless, this switch to 'Issuer Pays' introduced a new conflict of interest- would rating agencies be able to provide fair, unbiased evaluations of firms that were paying them?

As pointed out in Bolton et al. (2012), rating agencies have been blamed for a variety of market crashes from the Asian Financial Crash in 1997, to the collapse

of Enron in 2001 and WorldCom in 2002- both of which maintained Investment Grade status until days before declaring bankruptcy. This blame only intensified following the financial crisis of 2008. Commercial paper issued by Lehman Brothers was rated Investment Grade just before their default. Bolton goes on to highlight some of the main conflicts of interests inherently faced by rating agencies- first, issuers are paying the rating agencies. In addition, issuers have the option to have the rating not made public if they are not happy with the result.

2.2 Studies on Credit Rating Methodology

Pinches and Mingo (1973) wrote one of the earliest and most often cited papers in field of credit ratings. Their paper looks at statistical methods for predicting what rating a given firm might receive based on a set of variables (typically financial ratios). They apply a multiple discriminant analysis (MDA) to a set of issuers and using 7 factors (size, leverage, long term capital usage, short term capital usage, return on investment, earnings stability, and debt coverage). With this methodology they can predict close to 70% of bond ratings for a given year.

Six years later, Kaplan and Urwitz (1979) recap the prior literature and test both the MDA methodology as well as an ordinary least squares (OLS) multiple regression model. They find that the OLS method is sufficiently robust. In both papers, the data tended to focus on a single year rather than looking any trends of data over time.

Blume et al. (1998) is one of the first major papers to investigate the downward trend in credit ratings by examining the period from 1978 to 1995. They analyze a panel of Investment Grade firm data and create a credit rating model based on a variety of accounting metrics for each year.

The 6 variables used by Blume et al (1998) are primarily motivated by Standard and Poor's credit rating criteria, which mentions 10 Key Ratios; 5 of which relate to interest coverage, 3 relate to leverage, and 2 relate to profitability. Blume et al therefore include 'pretax interest coverage', 'operating income to sales', 'long-term debt to assets', and 'total debt to assets.' The first two of which should be positively correlated to improvements in credit rating and vice versa for the latter two. They also include a variable for 'firm size' which they find to have a positive correlation to credit ratings- the rationale being that larger firms tend to be older with more established product lines and more varied sources of revenues. They measure firm size by deflating the market value of the shares of the firm by the Consumer Price Index (CPI) and then they take the natural log of this inflation-adjusted measure. Finally, they include a Market Beta variable in keeping with past studies and based

on a hypothesis that 'a firm will be less able to service its debt for a given accounting ratio as its equity risk increases.' (Blume et al. 1998)

In their results, Blume et al (1998) take the coefficients of Year Dummies to be a measure of rating conservatism. They find that these annual intercepts did change over time, thus supporting the hypothesis that CRA standards were increasing over time.

Jumping forward a decade, Jorion et al. (2008) examine the same topic and reach some new and contrarian conclusions. First, they extend the time frame of the sample out until 2002 and include Speculative Grade firms (as opposed to Blume et al. (1998) which only included Investment Grade). Next, they replicate the Blume methodology across their data set by including variables for 'interest coverage', 'operating margin', 'long-term debt leverage', and 'total debt leverage'. They expect higher credit ratings for higher interest coverage, higher operating margin lower long-term and total debt leverage. They also include variables for firm market and beta. They find that while the trend of increasing conservatism is significant among Investment Grade firms, Speculative Grade firms show no such trend.

Jorion et al. (2008) go on to hypothesize that the downward trend in IG credit ratings is attributable to a factor not captured in the simple accounting metrics used in past analysis. They suggest that the increase in rating conservatism in IG names is actually due to a gradual decline in 'accounting quality'. They cite studies which show that as more CEOs have been focused on 'earnings management', the accuracy, quality and reliability of the accounting data published has become less reliable. This decline in accounting quality is observed primarily in IG names, and less so in SG names (which fits with the pattern seen in rating conservatism). When factoring in this decline in accounting quality, Jorion et al. (2008) conclude that this explains the overall decline in credit ratings- not an increase in conservatism by S&P.

In 2013, Aysun Alp, publishes a paper which again uses the Blume methodology as a base, but extends the window of sample data out to 1985-2007. Alp also looks at the findings of Jorion et al. 2008, and finds that during the 1985-2002 period, IG issues did show the effects of tightening credit rating standards, while SG names showed a loosening. However, he notes a regime change from 2002-2007, during which SG names experienced tightening and IG names saw an even faster pace of tightening. Alp attributes the apparent change in behavior of the rating agencies to increased regulatory scrutiny and investor criticism following the dot-com crash as well as some large-scale accounting scandals involving Enron and WorldCom.

Alp (2013) starts with the same explanatory variables as Blume et al. (1998), but adds several variables based on new reports issued by S&P to bring the total number of variables to 14. These include variables representing 'dividend payers', 'market to book', 'research and development', 'retained earnings', 'capital expenditures', 'cash balances', and 'tangibility'. He finds all of these to be statistically significant except for 'market to book'. He also finds the signs of the variable coefficients to be, for the most part, in-line with expectations: dividend payers tend to have higher ratings as they are generally less volatile and have more stable income streams, firms with more tangible assets and those with greater R&D spend also tend to be more highly rated.

The one unexpected result in the regression results of Alp (2013) is the negative sign for the coefficient of the variable representing cash holdings. Initially, one might assume that a high level of cash should translate to a low credit risk and thus a higher rating. However, in the work of Acharya, Davydenko, and Strebulaev (2011), they show that in many cases, firms expecting hard times often load up on 'precautionary cash holdings', which can provide some intuition as to why high levels of cash are seen to have a negative relationship to high credit ratings.

Alp (2013) also considers the relation between rating standards and default rates. He supposes that if ratings standards are getting tighter, the default rate for a given category should decline over time because the quality of firms in that rating pool increases. After regressing U.S. corporate default rates for each rating on a lagged measure of rating standards, he finds evidence to support his prediction- there does appear to be a negative relationship between rating standards and default rates (ie, as rating standards increase, and default rates decrease).

Finally, I build upon the work of Baghai et al. (2014), who build on the work of Blume (1998) and Alp (2013) while looking at the period 1985-2009, but expand to look at the implications of the increase in ratings conservatism with regards to capital structures and debt pricing. First, they establish that rating agencies have become more conservative over time, from 1985-2009. In doing so, they focus only on S&P rather than Moody's and Fitch, as they find that there exists a 94% correlation between the three agencies in terms of rating decisions.

As for the scope, they exclude certain sectors, which tend to have different capital structures from a typical corporate issuer (financials, utilities, and quasi-governmental sectors). They then set a numeric equivalent for each S&P rating with AAA set equal to 1 and C equal to 21. The variables used in the regression model come from previous research as well as the S&P guidelines and include: (1) total debt divided by total assets, (2) convertible debt divided by total assets, (3) rental payments divided by total assets, (4) cash and marketable securities divided by total

assets, (5) total debt divided by EBITDA, (6) EBITDA divided by interest payments, (7) EBITDA divided by sales, (8) profitability volatility, (9) the log of the book value of assets adjusted for inflation, (10) property, plant and equipment divided by total assets, (11) capital expenditures divided by total assets, (12) the firm's Beta, and (13) the firm's idiosyncratic risk.

They also see the somewhat counterintuitive effect of higher levels of cash being related to worse credit ratings, however, this phenomenon is explained by the 'precautionary motive for cash savings' put forth by Acharya, Davydenko, and Strebulaev (2012).

Baghai et al (2014) use an Ordinary Least Squares regression and look at the fixed effects by plotting the resulting coefficients of the Year Dummy Variables. These coefficients show an overall trend of increasing conservatism over the period in question. In addressing the contrarian views put forth by Jorion et al (2008), they create a new model which uses firm fixed effects- this model does show that increased ratings conservatism applies across both IG and SG firms. They also address the argument that the increase in conservatism must be related to some other element of soft information, which is not captured by the quarterly accounting data. If this was the case, they argue, the soft information would have to consistently be negative in its nature to explain the trend in credit ratings.

One possible explanation to justify the increased conservatism seen in the S&P ratings is that it is a direct result of a more challenging macro-economic environment, which could be measured by an increase in corporate default rates. Baghai et al (2014) test this possibility by looking at default rates over time and find that during the period in question, default rates trended lower in general (while moving with the business cycle). This is more evidence pointing to an unjustified increase in conservatism in rating agency behavior over time.

The two aims of this paper are a) to see if the trend of increase ratings conservatism identified in the literature continues beyond the financial crisis, and b) to see if this trend is present across all sectors. I extend the data set out through 2017 and follow a similar approach to that of Baghai et al. (2014). I exclude the financial, real estate, utility and quasi-government sectors and run an OLS regression against a set of variables, which includes most of the variables used by Baghai et al. (2014). In the end I find that the trend of increasing conservatism plateaus around 2007 and that all the sectors tested show an increase in rating conservatism in the subset of Investment Grade names.

3. Data

The data for this study is sourced from the Computstat database and consists of financial and accounting data as well as S&P ratings. I follow the same process described in Baghai et al. (2014) in that I create a universe of stocks by excluding Financials,[2] Utilities and Quasi-Sovereigns. I also exclude the Real Estate sector due to the small sample size available (only 72 firm-year data points over 30 years). I use one rating per firm, per year (as of January each year). I construct the variables using the latest reported date of each year (prior to the 'Rating Year'). For example, a rating published in January 2017 would be matched to fiscal year-end accounting data as of either April or December 2016- depending on the fiscal calendar used by a given firm.

To handle outliers in the data, I also follow the 'winsorizitaion' approach used in Baghai et al. (2014), in which for certain variables, extreme values are set to a 'max' of the 99th percentile observation and 'minimums' are set to the lowest 1st percentile value. This is detailed in the 'Data Preprocessing' section of the appendix. I only use S&P ratings as they cover the largest number of firms on average and as shown in, Baghai et al. (2014) the main three rating agencies have a correlation of 0.94 over the period from 1995 to 2009.

I select 11 explanatory variables based on past literature, primarily adhering to the methods used by Baghai et al. (2014): (1) 'Interest Coverage', (2) 'Profit', (3) 'Book Leverage', (4) 'Size', (5) 'Debt/EBITDA', (6) 'Negative Debt/EBITDA', (7) 'Cash/Assets', (8) 'Conv Debt/Assets', (9) 'Rent/Assets', (10) 'PPE/Assets', (11) 'CAPEX/Assets'. Again, more specific details on the construction of these variables can be found in the 'Data Processing' section of the Appendix (A.2).

Tables 1 shows a break-down of ratings by firm, per year. The average rating in 1986 was 8.99 (roughly equivalent to a rating of BBB) while in 2017, it rose to 11.15 (roughly equivalent to a rating of BB+). This equates to an average drop of 2 notches on the 21-point S&P rating scale over the time period. In 1986, 43% of firms have a rating better than BBB+ while in 2017, only 13% of firms fall into that category. It is clear from the data that the S&P credit ratings of U.S. corporates have declined.

[2] I attempt to separately apply the OLS Regression methodology to the Financial sector, however I find insignificant results, which I describe in Appendix 4.

Table 1

Number of Companies by Year and S&P Rating

This table shows the breakdown of companies by rating from 1986 to 2017. The ratings data was sourced from Computstat. Financial, Utility and Real Estate GICS sectors have been excluded.

	Rating									
Year	AAA	AA	A	BBB	BB	B	CCC	CC	C	Total
1986	28	109	212	124	145	178	9	1		806
1987	29	112	190	137	162	237	43			910
1988	30	111	182	128	180	284	36			951
1989	34	86	196	137	164	273	32			922
1990	34	84	186	149	163	246	31		1	894
1991	33	87	188	147	142	199	33	7		836
1992	30	86	194	157	149	165	31	9		821
1993	29	87	194	186	181	160	25	7	2	871
1994	27	83	194	203	239	193	14	1		954
1995	25	82	194	222	238	209	16			986
1996	25	78	213	235	255	232	17			1,055
1997	25	80	230	274	287	267	16	2		1,181
1998	25	78	232	316	317	313	15	4		1,300
1999	22	81	232	341	365	350	27	6		1,424
2000	16	71	215	362	368	404	40	6		1,482
2001	14	49	227	379	369	398	48	5		1,489
2002	12	48	219	390	363	365	64	7		1,468
2003	11	41	214	381	386	332	71	13		1,449
2004	11	38	200	372	403	372	56	6		1,458
2005	9	35	194	382	417	373	41	4		1,455
2006	9	34	200	348	397	356	45	2		1,391
2007	9	33	169	336	388	358	37	2		1,332
2008	7	35	155	321	358	354	22	3		1,255
2009	7	33	151	315	324	335	45	8		1,218
2010	5	31	142	324	292	346	43	4		1,187
2011	6	29	146	335	301	358	23	1		1,199
2012	6	28	146	335	323	341	23	1		1,203
2013	6	28	142	346	322	355	26			1,225
2014	6	34	140	350	341	341	25			1,237
2015	5	34	143	348	362	354	24	1		1,271
2016	5	32	128	349	352	293	41	6		1,206
2017	3	32	121	341	356	253	45	3		1,154
Total	543	1,909	5,889	9,070	9,409	9,594	1,064	109	3	37,590

Table 2 shows the average value for the dependent variable and 11 independent variables over time. The general trend of worsening ratings can be seen here as the average rating falls from 9.0 to 11.15 (just over 2 notches). Despite the worsening of the yearly average rating, the Interest Coverage shows an increasing trend over time- which should be considered as 'credit rating positive'.

Table 2: Variable Averages from 1986 to 2017

Below we see the average values of the variables used in the 'macro sample' multiple regression. We can see clearly that the average rating has gotten worse (numeric value has increased). Interest Coverage has increased as has Firm Size (inflation adjusted asset value),

Year	Rating	IntCov	Profit	Book_Lev	Size	Debt/ EBITDA	NegDebt/ EBITDA	Cash/ Assets	ConvDebt /Assets	Rent/ Assets	PPE/ Assets	CAPEX/ Assets
1986	9.00	7.91	0.16	0.33	7.34	3.51	0.037	0.081	0.041	0.020	0.64	0.087
1987	9.80	7.41	0.15	0.36	7.23	3.84	0.055	0.085	0.049	0.021	0.61	0.079
1988	10.08	7.29	0.17	0.38	7.27	3.75	0.043	0.088	0.056	0.020	0.57	0.073
1989	10.00	7.19	0.17	0.39	7.43	3.92	0.031	0.077	0.046	0.021	0.57	0.074
1990	9.93	6.80	0.17	0.41	7.52	3.79	0.035	0.069	0.039	0.020	0.59	0.074
1991	9.72	6.77	0.17	0.40	7.63	3.75	0.032	0.063	0.034	0.021	0.61	0.075
1992	9.54	6.29	0.16	0.40	7.67	3.98	0.028	0.064	0.034	0.021	0.64	0.068
1993	9.54	7.59	0.16	0.39	7.65	3.87	0.028	0.065	0.035	0.023	0.64	0.068
1994	9.71	8.44	0.16	0.38	7.58	3.74	0.023	0.069	0.036	0.022	0.63	0.070
1995	9.81	9.00	0.17	0.38	7.60	3.72	0.030	0.067	0.034	0.021	0.64	0.073
1996	9.90	9.35	0.17	0.39	7.60	3.40	0.034	0.067	0.028	0.020	0.68	0.078
1997	10.05	9.89	0.17	0.39	7.59	3.56	0.038	0.067	0.026	0.020	0.54	0.078
1998	10.23	10.16	0.18	0.40	7.58	3.63	0.047	0.074	0.028	0.020	0.65	0.083
1999	10.47	9.06	0.16	0.44	7.61	4.06	0.054	0.067	0.024	0.021	0.66	0.084
2000	10.79	8.41	0.16	0.45	7.61	4.34	0.061	0.070	0.021	0.020	0.63	0.070
2001	10.90	9.11	0.16	0.43	7.71	3.84	0.073	0.073	0.024	0.020	0.61	0.069
2002	10.92	9.03	0.16	0.42	7.78	4.16	0.058	0.075	0.024	0.021	0.63	0.065
2003	11.04	9.61	0.17	0.41	7.79	3.92	0.046	0.081	0.026	0.022	0.65	0.053
2004	11.10	10.99	0.17	0.39	7.86	3.97	0.029	0.090	0.026	0.021	0.64	0.050
2005	11.09	13.50	0.18	0.37	7.94	3.32	0.016	0.098	0.027	0.020	0.63	0.052
2006	11.08	14.86	0.19	0.36	7.99	3.25	0.015	0.096	0.022	0.019	0.61	0.057
2007	11.19	14.97	0.19	0.35	8.08	3.11	0.015	0.090	0.021	0.019	0.60	0.063
2008	11.15	13.67	0.19	0.36	8.21	3.30	0.023	0.087	0.020	0.018	0.59	0.064
2009	11.30	13.19	0.17	0.38	8.28	3.36	0.049	0.085	0.019	0.019	0.62	0.066
2010	11.34	11.90	0.17	0.37	8.28	3.79	0.046	0.105	0.018	0.020	0.64	0.050
2011	11.20	14.26	0.20	0.35	8.34	3.36	0.017	0.108	0.015	0.018	0.63	0.050
2012	11.11	14.63	0.21	0.36	8.38	3.31	0.015	0.099	0.012	0.017	0.61	0.057
2013	11.17	13.99	0.20	0.36	8.42	3.48	0.018	0.097	0.010	0.016	0.62	0.065
2014	11.15	13.79	0.20	0.37	8.44	3.57	0.023	0.100	0.009	0.016	0.63	0.063
2015	11.18	14.05	0.20	0.38	8.44	3.82	0.027	0.096	0.008	0.016	0.62	0.063
2016	11.18	12.67	0.16	0.40	8.46	3.66	0.075	0.094	0.007	0.016	0.65	0.057
2017	11.15	12.08	0.19	0.40	8.50	4.02	0.039	0.099	0.007	0.016	0.64	0.048
Mean	10.65	10.84	0.18	0.39	7.90	3.69	0.037	0.084	0.025	0.020	0.62	0.066
N	37,590	37,590	37,590	37,590	37,590	37,590	37,590	37,590	37,590	37,590	37,590	37,590

Table 3 shows the average values for the 11 independent variables by rating. Note the variables for 'Size', 'Interest Coverage', and 'Profit' appear to have a strong positive correlation with rating; ie, higher values for those terms correlate with higher firm ratings. Conversely, 'Book Leverage', 'Rent/Assets', and 'Debt/EBITDA' all show a strong negative correlation with rating.

Table 3: Non-Financial Firm, Summary Statistics by Rating

The table below shows the average value of each of the 11 variables used over the 31 years of observations from 1987 to 2017.

Rating	Int_Cov	Profit	Book_Lev	Size	Dt_Ebitda	NegDt_Ebitda	Cash_TA	ConDe_TA	Rent_TA	PPE_TA	CAPEX_TA
AAA	26.77	0.28	0.18	9.98	1.02	-	0.09	0.00	0.01	0.87	0.08
AA+	30.83	0.26	0.18	9.13	1.05	-	0.08	0.00	0.01	0.86	0.08
AA	22.65	0.25	0.21	9.54	1.27	0.00	0.07	0.00	0.01	0.83	0.08
AA-	26.55	0.25	0.23	9.35	1.48	0.00	0.09	0.01	0.01	0.75	0.07
A+	21.41	0.23	0.25	9.07	1.66	0.00	0.08	0.01	0.02	0.69	0.07
A	16.23	0.20	0.26	8.90	1.89	0.00	0.08	0.01	0.02	0.63	0.07
A-	16.12	0.21	0.26	8.95	1.99	0.00	0.08	0.01	0.01	0.64	0.07
BBB+	13.87	0.21	0.28	8.77	2.27	0.01	0.07	0.01	0.01	0.68	0.07
BBB	12.94	0.18	0.30	8.51	2.65	0.01	0.07	0.01	0.02	0.68	0.06
BBB-	11.69	0.17	0.30	8.35	2.92	0.01	0.08	0.02	0.02	0.60	0.06
BB+	10.70	0.18	0.34	7.99	3.15	0.02	0.09	0.02	0.02	0.60	0.06
BB	8.85	0.18	0.39	7.63	3.76	0.02	0.08	0.03	0.02	0.59	0.06
BB-	7.20	0.17	0.44	7.23	4.17	0.03	0.09	0.04	0.02	0.56	0.06
B+	5.34	0.16	0.54	6.73	5.29	0.04	0.08	0.04	0.02	0.53	0.06
B	3.75	0.13	0.58	6.80	6.20	0.09	0.09	0.03	0.03	0.60	0.07
B-	2.11	0.07	0.60	6.69	6.89	0.18	0.12	0.04	0.03	0.61	0.06
CCC+	0.94	0.07	0.69	6.64	7.98	0.26	0.09	0.04	0.03	0.65	0.06
CCC	1.55	0.06	0.73	6.27	8.66	0.21	0.08	0.03	0.03	0.69	0.05
CCC-	0.44	0.06	0.77	6.09	7.78	0.34	0.09	0.06	0.03	0.88	0.07
CC	1.33	0.09	0.74	6.51	7.40	0.24	0.08	0.01	0.03	0.76	0.06
C	0.36	0.12	1.03	6.44	22.63	-	0.03	-	0.02	0.36	0.02

4. Methodology

4.1) Macro Sample

I began with the scope of companies outlined in the data section (ie, exclusion of financial, real estate, utilities and quasi-government issuers and extreme outliers capped using winsorization). I follow a similar methodology to that of Baghai et al. (2014), who use an OLS multiple regression model. In their paper, they compare the results of the OLS model with that of Ordered Probit models used in Jorion et al. (2008) and Blume et al. (1998) and find that the OLS model produces similar results as Ordered Probit model. In addition, they find it easier to explain the economic significance of OLS results.

For the multiple regression model, the dependent variable is the S&P long term issuer rating[3] for a given firm. The independent variables are a selection of financial accounting metrics used in the work of Baghai et al. (2014) and are defined below:

[3] S&P uses a rating system which starts at AAA and goes to C (the rating of D or SD refer to 'default' or 'selective default' and is excluded from this study). The alpha rating convention is converted to a numerical equivalent (AAA = 1, C = 21).

1) ‘Interest Coverage’: EBITDA/ Interest Expenses

2) ‘Profit’: EBITDA/Revenue

3) ‘Book Leverage’: total debt/ total assets

4) ‘Size’: natural log of the book value of total assets adjusted for inflation into 2005 dollars

5) ‘Debt/EBITDA’: total debt/EBITDA

6) ‘Negative Debt/EBITDA’: 1 if ‘Debt/EBITDA’ is negative, otherwise set to 0

7) ‘Cash/Assets’: cash & marketable securities/ total assets

8) ‘Conv Debt/Assets’: total convertible debt/total assets

9) ‘Rent/Assets’: total rental expenses/ total assets

10) ‘PPE/Assets’: total property, plant & equipment / total assets

11) ‘CAPEX/Assets’: capital expenditures/ total assets

The motivation behind these variables is well summarized in the work of Baghai et al (2014), who explain that, ‘..firms have worse credit ratings when they have more debt of various kinds, pay higher rents, have lower interest cover, are less profitable, have more volatile profits, are smaller, hold more cash, have fewer tangible assets, have lower capital expenditures, and have negative debt to EBITDA ratios’.

These variables act as controls to capture any factors which might be influencing S&P’s ratings decision-making process. However, it should be noted that S&P often has access to non-public information, and they do not base their ratings decision strictly on quantitative data. The aim is to capture and control for as many firm-specific characteristics as possible in order to then determine whether time-varying effects exist.

In order to determine whether time-varying effects exist, I follow the approach of Baghai et al. (2014) in which they create dummy-variables for each year in the sample. The idea is to see if the coefficients for the dummy-variables remain constant over time or demonstrate a trend (an upward trend indicates an increasing level of conservatism in S&P ratings and vice versa). I then run an OLS Regression with the numeric rating score as the dependent variable and the 11 financial metrics and Year Dummy Variables as the independent variables. Note, when generating the Year Dummy Variables, the first year of the sample (1986) does not have an associated dummy variable.

Equation 1: Ordinary Least Squares Regression Equation

$$\hat{Y} = b_0 + \sum_k X_k + \sum_y Dy$$

$$\hat{Y} = dependent\ variable\ (rating\ score)$$

$$b_0 = \ y\ intercept$$

$$\sum_k X_k = \ independent\ variables\ (firm\ fundamental\ metrics)$$

$$\sum_y Dy = \ independent\ variables\ (year\ dummy\ variables)$$

I plot the year dummy variable coefficients along with their 95% confidence interval values. If the coefficient increases by 1, this can be interpreted as a 1 notch implied downgrade by S&P. In other words, while holding firm characteristics constant, a firm that was rated AA- in a given year would now be rated A+ the later year. The year dummy coefficient plot shows an upward slope and resembles those of previous studies (Blume et al. (1998), Jorion et al. (2008), Baghai et al. (2014)) for the periods of overlapping analysis. The latest year of data used in previous studies was in Baghai et al. (2014), which was 2007, while this paper extends the set out through 2017. To check for significance, I plot the 'year dummy coefficients' alongside a 95% confidence interval band. I use 'robust' standard errors to compensate for the heteroskedasticity of the data set.

4.2) Investment Grade vs Speculative Grade

For the next section of analysis, I follow an approach first seen in the work of Jorion et al. (2008). They show that although rating criteria have generally been increasingly stringent throughout the period of 1985- 2002, there exists a split between Investment Grade (IG) and Speculative Grade (SG) firms, whereby IG firms are impacted, while SG firms are not.

To test whether this pattern continues beyond 2002, I split the initial set of firms into IG and SG samples (SG = rating below BBB-) and run two multiple regressions as described in the previous section. I then plot the year dummy coefficients for IG and SG firms along with their respective 95% confidence interval bands. During the overlapping period, my results look to be in line with those of Jorion et al. (2008).

4.3) Analysis by Sector

In order to determine if time-vary effects of rating stringency impact some sectors more than others, I repeat the above procedures while controlling for 'Sector' (as

defined by the Global Industry Classification Standards- GICS). I start with the original data set used in section 4.1, I run an OLS regression for each sector; once again with the same 11 financial variables as well as year-dummies. I test for the effects of increased conservatism across the following 8 sectors: Energy, Materials, Consumer Discretionary, Consumer Staples, Health Care, Information Technology, and Communication Services (GICS: 10, 15, 20, 25, 30, 35, 45 and 50 respectively).

In addition to running a regression for each sector, I also apply an Investment Grade versus Speculative Grade split in order to see if the findings of Jorion et al. (2008) exist across all sectors. I run 24 regressions; one for each of the 8 sectors, as well as IG and SG splits by sector- this level of analysis is not done in any of the reviewed literature.

5. Results

5.1) Macro Sample

The first regression is run on the 'macro sample' of all in-scope firms and generates an R-Squared value of 0.63. The full results of the regression are presented in Table 5. By looking at the sign of each coefficient we can make an interpretation as to how a given variable is correlated with a firm's rating. Since I use the numeric convention of 1 to represent the best rating and 21 to represent the worst, we consider a negative sign to be related to a better credit rating (and vice versa). The results make intuitive sense for the most part. The coefficients for 'Interest Coverage', 'Profit' and 'Size' all have a negative sign, i.e., a higher value for these variables leads to a lower numeric rating score, which equates to a 'better' rating.

The coefficients for the 'Book Leverage', 'Debt/EBITDA' and 'Rent/Total Assets' variables, on the other hand are positive, as expected. This also makes intuitive sense as higher values for these metrics imply higher fixed financial obligations, which increase the likelihood of default.

The resulting coefficients for 'Cash/Total Assets' are not as intuitive, but again can be partially explained by Acharya, Davydenko, and Strebulaev (2012). Their work sheds light onto why holding high levels of cash be a negative characteristic in terms of a firm's rating.

The coefficients of year dummies are taken as a proxy for the level of conservatism of the S&P rating methodology. The idea being that if S&P maintains a consistent level of conservatism and we hold the financial ratio coefficients constant, the year dummy coefficients should be zero. For example, let's imagine a hypothetical case; a firm with a rating of 9 in 1999- we move forward in time by one year and assume that there is no change to any of the firm's financial ratios. If, in the following year, the firm's rating was increased to 10 (implying a one-notch

downgrade), this would correspond to an increase of the year-dummy coefficient of 1.

In this case of the OLS regression run on the macro sample of firms, the year dummy coefficient increases by 3 from 1986 to 2017, implying an increase in conservatism by S&P of three notches. The year-dummy coefficients show the steepest increase from 1999 to 2007 and continue to increase until 2011 at which point the coefficients appear to plateau.

5.2) Investment Grade vs Speculative Grade

The work of Jorion et al. (2008) finds a clear split between Investment Grade (IG) and Speculative Grade (SG) issuers in terms of ratings conservatism over time. During their period of study (1985- 2002), they note that SG issuers show no discernable trend in their time varying coefficients, while IG firms, do show an increase in conservatism.

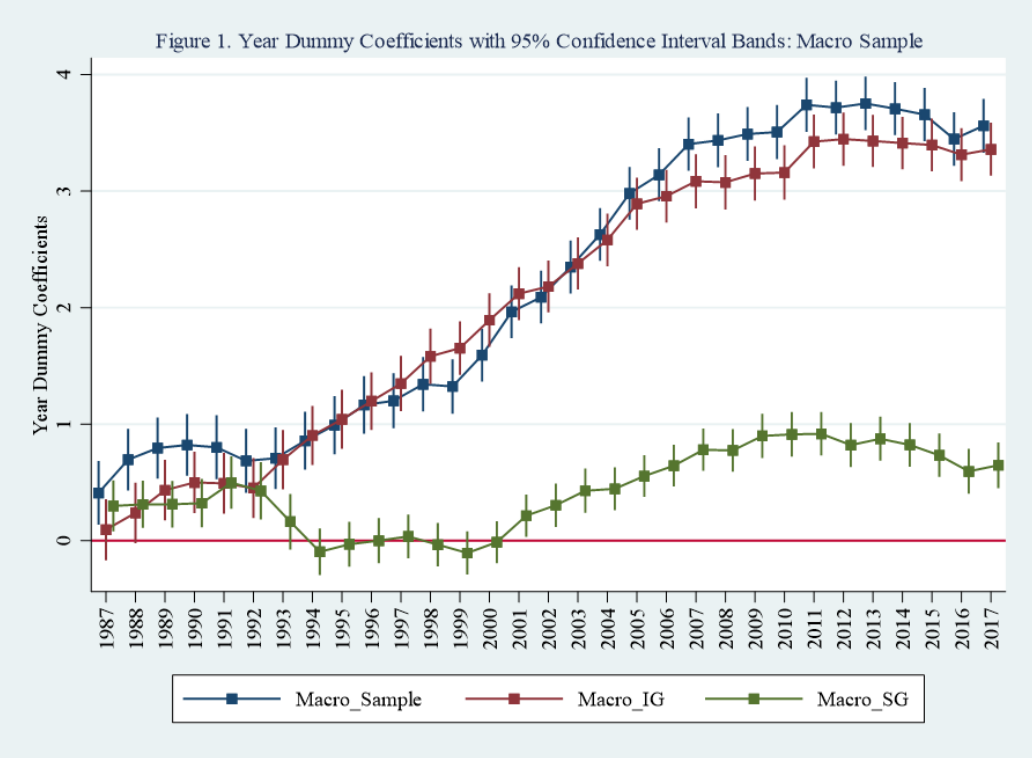
Beginning with the same dataset as in the previous section, I run two additional regressions; one for IG and one for SG firms. The number of IG firm-year observations is 17,409 and for SG 20,146. For the most part, the sign of the coefficients is the same across the Macro Sample, the Macro_IG Sample and the Macro_SG sample, however a few exceptions appear. For the Cash/Total Assets variable, we see a negative sign for IG names and vice versa for SG names. This implies that the concept of 'protective cash holdings' explained by Acharya, Davydenko, and Strebulaev (2012) applies to lower rated firms, but for a highly rated firm to holding a large amount of cash is not taken as a bad thing.

From 1985-2002, the results are in-line with those of Jorion et al. (2008); there is an increase in the year-dummy coefficients in the IG set, while the SG set shows no trend. However, in the years following their research (2003-2017), there is a slight increase in conservatism within the SG set of firms by nearly one-notch. As seen with the previous example, the trend seems to level off from 2007 through 2017.

The plot of the year-dummy coefficients for IG vs SG firms is seen in Figure 1 (alongside the plot of the year-dummy coefficients for the entire sample). Based on the year-dummy approach, we can say that from 1987 to 2017, an Investment Grade firm with the same accounting metrics has close to a 3.5 notch downgrade, while a Speculative Grade firm sees just less than a full notch of a downgrade. The R-Squared values for both the Investment Grade and Speculative Grade, are (0.39) and (0.35) respectively.

Figure 1. Plot of coefficients of year dummies from Macro Sample OLS Regression

In the graph below I plot three series of year dummy coefficients over time. One for the overall sample of firms, a second for the Investment Grade subset of firms, and a third for the Speculative Grade subset of firms.



5.3) Analysis by Sector

In order to check whether the increase rating standards is being driven by a particular group of sectors, another set of 24 regressions is run in which the initial 'macro sample' data set is segregated both by Investment/Speculative Grade and by GICS Industry Code[4]. The same multiple regression is run using the same 11 independent variables and year-dummy variables, however, now the data was split into the following sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Information Technology, and Communication Services. Each of these sectors is further split into IG/SG firms, so for each sector I first run a regression across all firms in that sector, followed by two more regressions- with IG and SG isolated, resulting in a total of 3 regressions per sector.

Upon running the 24 sector regressions, we do see a similar pattern emerge in that the coefficients for the year dummy variables once again do show an upward

[4] GICS or Global Industrial Classification Standards use a series of 2-digit codes to represent a firm's sector. The sectors which were analyzed were: 10- Energy, 15- Materials, 20- Industrials, 25- Consumer Discretionary, 30- Consumer Staples, 35- Health Care, 45- Information Technology, and 50- Communication Services.

trend over time for both each complete sector as well as for the IG-only set within each sector. As for the SG-only sector regressions, for the most part, the findings of Jorion et al. (2008) do hold- up until 2002, there does not appear to be any significant increase in ratings conservatism among SG names, regardless of the sector.

However, after 2002, we do see a couple of possible exceptions to this rule; the communication services sector exhibits a large (2 notch) increase in rating stringency following the WorldCom default (which makes intuitive sense). Both the consumer staples and consumer discretionary sectors also show an increase in stringency within their SG names from around the year 2000 to the year 2008; following the financial crisis, it does seem as though this small trend of increased standards is reversed a bit.

The largest effect is seen with the Investment Grade names, which show an increase in ratings conservatism across all sectors. Communication Services and IT sector show an impact of nearly 4 notches within their investment grade names over the observation period.

The plots of these regressions are in Figures 2-9 and contain results for the 'full sector', 'IG sector', and 'SG sector' regressions; plotted alongside 95% confidence intervals. The full results of these regression are seen in Table 4.

Table 4: Regression Summary

The table below shows the results of 11 OLS Regressions and include 11 financial independent variables as well as year dummy variables. The Robust Standard Errors for each coefficient are in parentheses below. The asteriks denote statistical significance via p-value with *** p<0.01, ** p<0.05, * p<0.1.

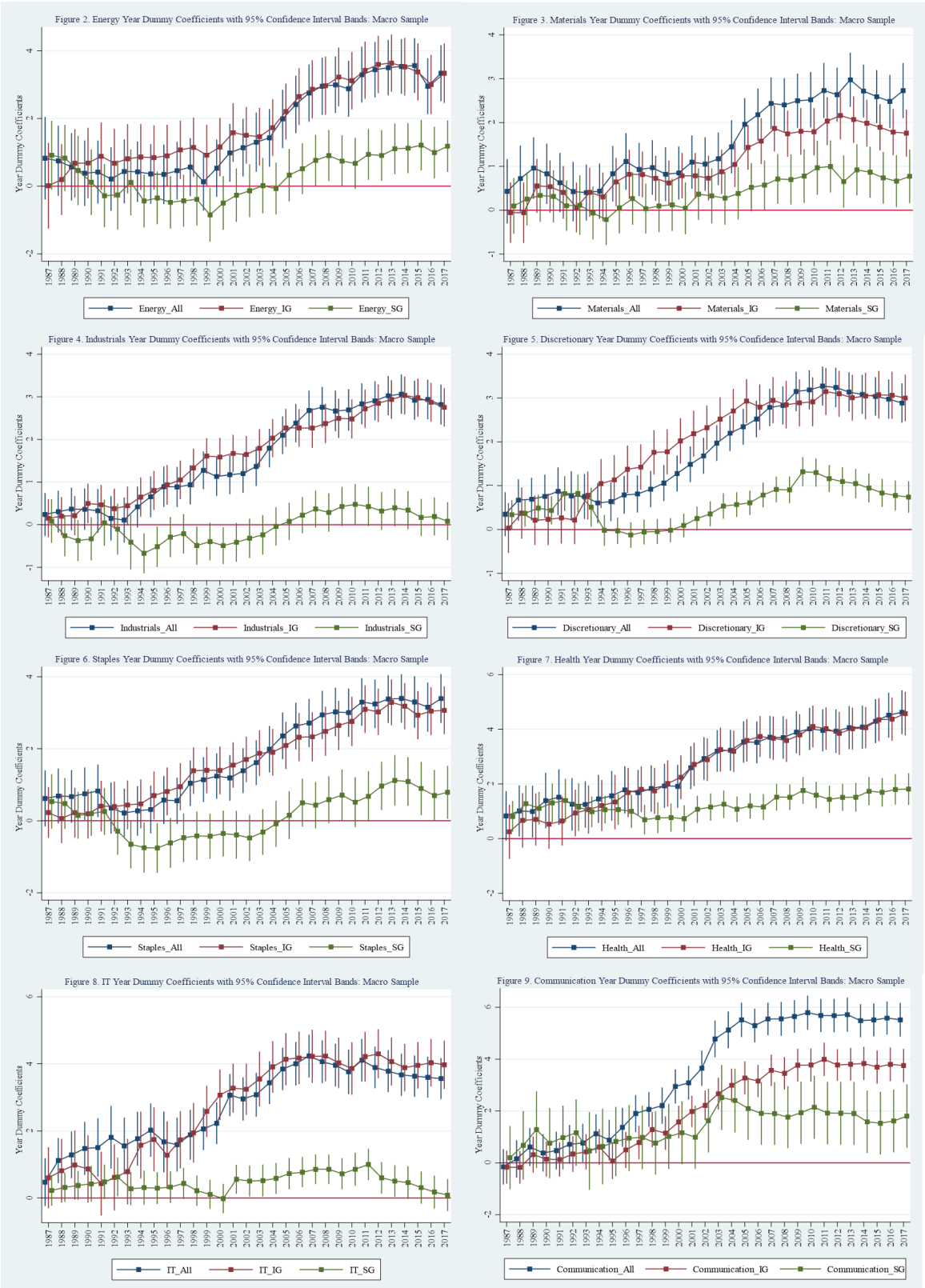
Variable	Macro All	Macro IG	Macro SG	Energy All	Materials All	Industrials All	Discretionary All	Staples All	Health All	IT All	Comm. All
Int_Cov	-0.018***	-0.016***	-0.004***	-0.022***	-0.036***	-0.027***	-0.026***	-0.025***	-0.011***	-0.014***	-0.006
	(0.003)	(0.001)	(0.001)	(0.003)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)	(0.004)
Profit	-1.292***	-2.011***	-0.162*	0.787***	0.042	-2.629***	-0.411	-7.946***	-4.225***	-3.108***	-3.808***
	(0.114)	(0.134)	(0.087)	(0.199)	(0.446)	(0.256)	(0.282)	(0.589)	(0.427)	(0.392)	(0.463)
Book_Lev	3.433***	1.599***	1.495***	2.266***	4.490***	4.723***	2.658***	4.020***	4.010***	2.229***	4.294***
	(0.106)	(0.160)	(0.050)	(0.230)	(0.209)	(0.195)	(0.126)	(0.249)	(0.272)	(0.240)	(0.222)
Size	-1.239***	-0.699***	-0.467***	-1.608***	-1.138***	-1.077***	-1.128***	-1.293***	-1.583***	-1.439***	-0.819***
	(0.010)	(0.013)	(0.010)	(0.030)	(0.028)	(0.024)	(0.019)	(0.030)	(0.033)	(0.033)	(0.029)
Dt_Ebitda	0.179***	0.184***	0.087***	0.095***	0.155***	0.171***	0.163***	0.157***	0.153***	0.096***	0.163***
	(0.005)	(0.014)	(0.003)	(0.009)	(0.011)	(0.011)	(0.008)	(0.022)	(0.022)	(0.012)	(0.013)
NegDt_Ebitda	2.348***	0.542***	1.885***	1.724***	2.599***	2.266***	2.586***	0.611	1.012***	1.050***	2.161***
	(0.097)	(0.181)	(0.069)	(0.202)	(0.236)	(0.269)	(0.182)	(0.688)	(0.391)	(0.229)	(0.358)
Cash_TA	0.347*	-1.359***	0.640***	0.169	1.105**	1.528***	-1.313***	-2.298***	-3.193***	0.331	1.492***
	(0.182)	(0.174)	(0.098)	(0.458)	(0.504)	(0.412)	(0.289)	(0.558)	(0.401)	(0.279)	(0.536)
ConDe_TA	2.753***	4.188***	-0.396***	0.954	3.876***	0.780	1.724***	2.932***	1.648***	2.091***	5.522***
	(0.194)	(0.368)	(0.125)	(0.590)	(0.723)	(0.529)	(0.363)	(0.705)	(0.446)	(0.384)	(0.936)
Rent_TA	7.826***	10.499***	3.345***	2.407	-18.806***	20.649***	5.228***	22.924***	-0.539	-8.055***	13.384***
	(0.433)	(0.620)	(0.321)	(1.967)	(3.738)	(1.107)	(0.524)	(1.867)	(2.067)	(2.409)	(2.266)
PPE_TA	-0.463***	-0.319***	0.227***	0.107	-0.019	-0.254***	-0.712***	-1.674***	-0.700***	-0.410***	-1.361***
	(0.040)	(0.047)	(0.031)	(0.095)	(0.099)	(0.097)	(0.076)	(0.156)	(0.202)	(0.142)	(0.122)
CAPEX_TA	1.990***	1.100***	-0.484**	0.521	-7.316***	-3.346***	0.546	-10.879***	-4.003**	6.154***	2.497**
	(0.279)	(0.381)	(0.193)	(0.452)	(0.902)	(0.654)	(0.549)	(1.551)	(1.555)	(1.181)	(1.071)
_1987	0.410***	0.094	0.297***	0.825	0.431	0.239	0.348	0.620	0.833*	0.475	-0.152
	(0.139)	(0.134)	(0.111)	(0.622)	(0.375)	(0.256)	(0.256)	(0.397)	(0.461)	(0.363)	(0.348)
_1988	0.694***	0.238*	0.311***	0.748	0.721*	0.306	0.671***	0.688*	1.013**	1.118***	0.153
	(0.135)	(0.133)	(0.104)	(0.529)	(0.386)	(0.252)	(0.242)	(0.390)	(0.477)	(0.343)	(0.367)
_1989	0.794***	0.433***	0.312***	0.572	0.961***	0.367	0.692***	0.674*	0.989**	1.287***	0.612
	(0.134)	(0.133)	(0.102)	(0.508)	(0.358)	(0.255)	(0.249)	(0.374)	(0.483)	(0.354)	(0.375)
_1990	0.821***	0.499***	0.321***	0.384	0.830**	0.364	0.757***	0.751**	1.392***	1.478***	0.384
	(0.135)	(0.134)	(0.106)	(0.494)	(0.351)	(0.248)	(0.252)	(0.372)	(0.520)	(0.404)	(0.367)
_1991	0.801***	0.491***	0.497***	0.419	0.630*	0.326	0.871***	0.830**	1.519***	1.505***	0.474
	(0.140)	(0.133)	(0.115)	(0.475)	(0.345)	(0.262)	(0.279)	(0.372)	(0.518)	(0.445)	(0.371)
_1992	0.684***	0.451***	0.427***	0.210	0.425	0.150	0.766***	0.351	1.256**	1.812***	0.713*
	(0.140)	(0.131)	(0.125)	(0.479)	(0.346)	(0.265)	(0.287)	(0.363)	(0.490)	(0.476)	(0.381)
_1993	0.707***	0.695***	0.162	0.438	0.402	0.110	0.753***	0.217	1.252***	1.553***	0.768**
	(0.135)	(0.130)	(0.122)	(0.483)	(0.327)	(0.271)	(0.263)	(0.344)	(0.435)	(0.431)	(0.378)
_1994	0.857***	0.903***	-0.096	0.426	0.435	0.417*	0.605***	0.274	1.454***	1.769***	1.124***
	(0.127)	(0.130)	(0.102)	(0.455)	(0.321)	(0.246)	(0.233)	(0.351)	(0.447)	(0.409)	(0.383)
_1995	0.990***	1.041***	-0.032	0.362	0.833**	0.656***	0.637***	0.315	1.564***	2.025***	0.877**
	(0.127)	(0.129)	(0.099)	(0.451)	(0.324)	(0.245)	(0.228)	(0.338)	(0.466)	(0.406)	(0.401)
_1996	1.164***	1.197***	-0.000	0.350	1.112***	0.892***	0.788***	0.577*	1.786***	1.674***	1.370***
	(0.126)	(0.127)	(0.099)	(0.448)	(0.329)	(0.243)	(0.219)	(0.340)	(0.443)	(0.461)	(0.383)
_1997	1.200***	1.348***	0.035	0.457	0.928***	0.887***	0.811***	0.556*	1.685***	1.593***	1.904***
	(0.121)	(0.121)	(0.095)	(0.436)	(0.311)	(0.240)	(0.215)	(0.330)	(0.421)	(0.410)	(0.365)
_1998	1.342***	1.582***	-0.035	0.566	0.973***	0.935***	0.920***	1.043***	1.832***	1.885***	2.062***
	(0.120)	(0.121)	(0.095)	(0.437)	(0.318)	(0.235)	(0.211)	(0.324)	(0.435)	(0.379)	(0.342)
_1999	1.323***	1.653***	-0.107	0.130	0.822***	1.277***	1.060***	1.144***	1.930***	2.061***	2.207***
	(0.120)	(0.117)	(0.094)	(0.435)	(0.313)	(0.225)	(0.210)	(0.318)	(0.411)	(0.321)	(0.357)
_2000	1.592***	1.892***	-0.014	0.532	0.849***	1.130***	1.277***	1.240***	1.914***	2.229***	2.946***
	(0.115)	(0.117)	(0.092)	(0.431)	(0.308)	(0.232)	(0.209)	(0.322)	(0.402)	(0.318)	(0.335)
_2001	1.964***	2.120***	0.214**	0.986**	1.098***	1.173***	1.489***	1.191***	2.594***	3.069***	3.090***
	(0.116)	(0.116)	(0.093)	(0.437)	(0.311)	(0.233)	(0.208)	(0.323)	(0.402)	(0.320)	(0.332)
_2002	2.090***	2.181***	0.303***	1.136***	1.054***	1.201***	1.681***	1.392***	2.928***	2.956***	3.651***
	(0.116)	(0.113)	(0.095)	(0.435)	(0.312)	(0.232)	(0.209)	(0.317)	(0.398)	(0.329)	(0.346)
_2003	2.349***	2.379***	0.428***	1.302***	1.173***	1.367***	1.971***	1.615***	3.206***	3.080***	4.779***
	(0.116)	(0.114)	(0.097)	(0.446)	(0.306)	(0.234)	(0.209)	(0.319)	(0.388)	(0.333)	(0.361)
_2004	2.628***	2.581***	0.445***	1.428***	1.448***	1.798***	2.196***	1.988***	3.229***	3.437***	5.129***
	(0.115)	(0.115)	(0.094)	(0.435)	(0.309)	(0.231)	(0.206)	(0.330)	(0.382)	(0.326)	(0.362)
_2005	2.981***	2.891***	0.554***	1.990***	1.963***	2.099***	2.344***	2.358***	3.538***	3.845***	5.517***
	(0.115)	(0.114)	(0.091)	(0.439)	(0.303)	(0.227)	(0.208)	(0.332)	(0.386)	(0.323)	(0.338)
_2006	3.141***	2.957***	0.643***	2.416***	2.180***	2.384***	2.521***	2.633***	3.522***	4.004***	5.294***
	(0.116)	(0.115)	(0.091)	(0.432)	(0.304)	(0.229)	(0.213)	(0.331)	(0.390)	(0.330)	(0.332)
_2007	3.404***	3.085***	0.779***	2.752***	2.439***	2.682***	2.787***	2.716***	3.709***	4.233***	5.549***
	(0.117)	(0.119)	(0.092)	(0.432)	(0.303)	(0.236)	(0.217)	(0.341)	(0.397)	(0.327)	(0.321)
_2008	3.436***	3.076***	0.774***	2.954***	2.401***	2.757***	2.831***	2.941***	3.698***	4.064***	5.554***
	(0.118)	(0.119)	(0.093)	(0.431)	(0.312)	(0.242)	(0.222)	(0.341)	(0.397)	(0.325)	(0.333)
_2009	3.491***	3.151***	0.898***	2.995***	2.498***	2.669***	3.149***	3.023***	3.892***	3.961***	5.649***
	(0.118)	(0.119)	(0.097)	(0.426)	(0.316)	(0.243)	(0.229)	(0.343)	(0.394)	(0.325)	(0.321)
_2010	3.507***	3.159***	0.912***	2.881***	2.520***	2.693***	3.186***	3.003***	4.013***	3.761***	5.795***
	(0.118)	(0.119)	(0.098)	(0.421)	(0.324)	(0.248)	(0.228)	(0.341)	(0.392)	(0.339)	(0.334)
_2011	3.741***	3.425***	0.917***	3.295***	2.732***	2.836***	3.273***	3.298***	3.964***	4.109***	5.684***
	(0.118)	(0.118)	(0.095)	(0.421)	(0.321)	(0.246)	(0.227)	(0.339)	(0.393)	(0.324)	(0.325)
_2012	3.717***	3.447***	0.820***	3.443***	2.637***	2.907***	3.242***	3.247***	3.931***	3.891***	5.680***
	(0.118)	(0.117)	(0.096)	(0.418)	(0.314)	(0.234)	(0.230)	(0.345)	(0.406)	(0.316)	(0.330)
_2013	3.753***	3.431***	0.874***	3.502***	2.977***	3.027***	3.137***	3.382***	4.059***	3.782***	5.717***
	(0.117)	(0.115)	(0.096)	(0.417)	(0.316)	(0.235)	(0.231)	(0.340)	(0.403)	(0.319)	(0.335)
_2014	3.708***	3.413***	0.821***	3.541***	2.720***	3.064***	3.083***	3.397***	4.077***	3.672***	5.484***
	(0.116)	(0.115)	(0.096)	(0.413)	(0.309)	(0.235)	(0.228)	(0.344)	(0.404)	(0.322)	(0.325)
_2015	3.657***	3.396***	0.732***	3.565***	2.593***	2.922***	3.037***	3.299***	4.296***	3.631***	5.514***
	(0.116)	(0.116)	(0.095)	(0.412)	(0.309)	(0.234)	(0.224)	(0.365)	(0.409)	(0.314)	(0.323)
_2016	3.447***	3.313***	0.594***	2.954***	2.483***	2.937***	2.976***	3.156***	4.516***	3.599***	5.588***
	(0.117)	(0.116)	(0.098)	(0.421)	(0.309)	(0.238)	(0.228)	(0.349)	(0.421)	(0.312)	(0.326)
_2017	3.561***	3.359***	0.647***	3.338***	2.729***	2.818***	2.887***	3.394***	4.625***	3.561***	5.519***
	(0.118)	(0.116)	(0.100)	(0.422)	(0.321)	(0.240)	(0.229)	(0.348)	(0.410)	(0.313)	(0.333)
Constant	16.431***	11.163***	15.071***	20.537***	16.562***	15.191***	16.948***	18.445***	19.448***	18.878***	11.934***
	(0.138)	(0.141)	(0.106)	(0.507)	(0.366)	(0.280)	(0.240)	(0.393)	(0.456)	(0.399)	(0.405)
Observations	37,555	17,409	20,146	4,184	4,935	7,017	8,401	3,354	3,004	3,314	3,346
R-squared	0.632	0.393	0.351	0.720	0.600	0.630	0.618	0.712	0.768	0.679	0.763

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figures 2-9. Plot of coefficients of year dummies from by-sector OLS Regression

In the 8 graphs below (one for each in-scope sector), I plot the year-dummy coefficients for a) the entire sector b) the investment grade names of a given sector and c) the speculative grade names of the same sector. The plots inclue a 95% confidence interval band.



6. Conclusion and Implications

6.1) Macro-Sample

The first section of analysis seeks to reproduce the results of past studies and to continue the analysis forward in time to see if the previously observed trends continue. With regards to the first goal, the past results are in line with those observed using the OLS Multiple Regression methods used by Baghai et al. (2014). Based on the year-dummy coefficient measure, it appears that S&P has increased their level of conservativeness from 1987-2007.

As for the continuation of the trend, we see that this trend appears to stop after 2007. The overall increase of conservatism reaches 3 notches by 2007, but from then on, remains within the 3 to 3.5 range. To put this in context, if a firm with the exact same balance sheet, interest coverage and profitability had a rating of BBB (Investment Grade) in 1986, that firm would receive a rating of BB (Speculative Grade) in 2017.

The results appear to be significant when overlaying 95% confidence interval bands to the plot of year-dummy coefficients, we see that the lower bound remains well above zero. Statistically speaking, the null hypothesis is that the coefficient of the year dummy variables is equal to zero. When looking at the resulting coefficients, we can say with 95% confidence that the coefficients are not equal to zero and thus reject the null hypothesis.

Jorion et al (2008) suggest that a possible explanation for this observed increase in conservatism is actually due to the change in accounting quality over time. As more and more focus has been placed on a firm meeting (or beating) their quarterly earnings expectations, the theory states that CEOs and CFOs have made efforts to smooth or modify their financial results. They propose that due to an increase of this ‘earnings management’ the overall quality of accounting data had worsened over time. They cite Duffie and Lando (2001) who show that imprecision of accounting measures of a given firm leads to higher levels of default risk. Jorion et al (2008) suggest that when this decline in accounting data quality is taken into consideration, the increase in ratings conservatism becomes insignificant.

Another argument against the hypothesis that S&P has been increasing its level of conservatism over the years suggests that this perceived ‘increase’ is really due to non-measurable ‘soft information’ about a given firm, or perhaps the non-public information to which S&P has access. Baghai et al (2014) address this by pointing out that if this were in fact the case, the ‘soft information’ incorporated to this new regime of ratings would all have to be consistently and overwhelmingly negative to produce such a trend.

6.2) Investment Grade vs Speculative Grade Firms

The aim of this portion of the analysis is to see if the findings of Jorion et al (2008) could first, be replicated, and second- would this trend be shown to continue beyond 2002 (the last year included in Jorion's paper)?

To the first point, yes, the results of this paper are in agreement with those of Jorion et al. (2008). In both cases, a clear bifurcation between Investment Grade and Speculative Grade year-dummy coefficients appears to exist.

As for the second point, when I extend the analysis from 2002 through 2017, I observe that Speculative Grade firms are not immune from increased ratings conservatism. In fact, from 2000 to 2009, it appears that Speculative Grade names experienced the effect of a full 1-notch downgrade, while accounting for fixed-firm effects and considering the 95% confidence interval around the year-dummy coefficients. This trend in SG plateaus around 2009 and is quite small in comparison to the trend in IG names which see more than a 3-notch increase in ratings conservatism. As with the SG names, the IG trend tends to plateau around 2007 through 2017.

Why might S&P increase their level of conservatism? If we consider their incentives, they might view the consequences of being 'too lenient' to be worse than the consequences of being 'too conservative'. In the case of being 'too lenient' firms would be happy to have a generous rating, but investors would suffer more 'Investment Grade' defaults- which could lead to possible litigation. However, in the case of being 'too conservative', while some corporates might complain about their 'unfair' rating, there would be fewer 'investment grade' defaults, and thus a reduced risk of facing a massive lawsuit.

As for the speculative name ratings, S&P has been fairly consistent for the duration of the 30-year rating history covered in this paper, suggesting perhaps that obviously risky debt might be easier to identify and thus a change to their methodology was not warranted. Again, S&P have not made any statements confirming any such change to their methodology, so we can only speculate.

6.3) Sector Analysis

The analysis at Sector level shows similar patterns as seen with the wider scope of corporate issuers. Each sector did show an increase in conservatism from 1987-2007, followed by a plateau from 2008-2017. While most sectors were clustered together, showing around a 2-3 notch increase in conservatism, the 'Communication Services' sector saw the steepest increase, a 6-notch increase, which mainly occurred from 1995-2005. Again, to put this in context, a firm rated

‘A’ in 1995 would receive a rating of ‘BB+’ in 2005- going from comfortably Investment Grade, to Speculative Grade.

This could be related to structural changes in the Communication Services sector. From 1995 to 2005, that sector saw a large amount of consolidation among long-standing, highly rated telecoms as well as the introduction of many new players following the dotcom boom. Additionally, the large-scale failure of World Com likely had a knock-on effect to the way telecoms were rated going forward.

When conducting the same Investment Grade vs Speculative Grade analysis on a sector by sector level. The pattern is consistent across sectors- the bulk of the increase of conservatism occurs within Investment Grade names, while the Speculative Grade names are less affected.

6.4) Implications

In general, a low rated firm will have to pay a much higher price to issue debt in the market (represented by the yield of their debt at the time of issuance). Thus, the cumulative impact of US Corporate ratings being ‘3 notches too low’, could be huge. However, there are a couple of factors which might offset this impact. First, as interest rates have been falling over the past decade, investors have been desperate to purchase any positively yielding assets. As government debt goes to negative yields in some cases, this has an overall impact of yield compression across corporate debt. Investors go further out on the spectrum of risky debt and as they do, they have the effect of lowering the cost of debt for these risky issuers in the future.

Second, the market is becoming more and more skilled at using non-traditional sources of information to price securities. Perhaps, 30 years ago, before the days of the internet, the importance of a rating by S&P would have been the single determining factor of a bond’s yield. Now the corporate traded credit market is very developed across the banking and hedge fund sectors- each armed with their own team of credit analysts pouring through not only corporate earnings releases, but also looking at big data and drawing conclusions based on non-traditional sources of data (satellite imagery of parking lots outside of shopping malls, is one often cited example). As a result, if S&P are in fact mis-rating corporate debt today, the full impact of this won’t be felt by the issuers. Rather, the collective opinion of the market and the supply/demand dynamics of investors will set the price of a given corporate’s debt.

Baghai et al. (2014) examine the impact of increased ratings stringency on debt spreads in order to determine whether markets take into account the increase in conservatism when determining the cost of debt. They look at actual ratings (which

are ‘too conservative’) versus predicted ratings and they find that capital markets undo more than one-fifth of the overall impact of conservatism. In other words, when a rating is unfairly severe, the market ‘knows better’ and doesn’t fully penalize the firm by charging then a cost of debt equivalent to their overly conservative rating.

In summing up, the increase in conservatism for Investment Grade names does appear to have levelled off post-2007. A precise motivation for why exactly the S&P would have increased their standards from 1987-2007 remains unclear. Similarly, one can only speculate as to why the standards then appear to level off from 2007 onward.

One possibility might be related to the passage of new regulation in the US in December 2008. These new regulations require rating agencies to provide greater transparency and reveal details on their methodologies to regulators (White, 2010). Could it be that since rating agencies have been compelled to provide the ‘secret formula’ to their rating methodology, they are now unlikely to change those methods?

7. Outlook for Further Research

The scope of this paper focuses on a large time frame and looks into firm-effects based on investment grade vs speculative grade as well as sector-level effects. The analysis shows that in general, little-to-no effect is observed for speculative names. Future research could exclude these firms from the scope of the study and perhaps go into a more granular level on a rating-specific level of detail (ie, AAA vs AA vs A, etc).

Additionally, there could be a further dive into the observed frequency of defaults in the market and how those could have impacted rating agency behavior. The inherent problem being that with such a relatively low number of observations of defaults, and with those observations generally hitting low-rated names, it is difficult to draw conclusions.

Perhaps CDS-Spread levels or Corporate Bond yields could be looked at as the market’s implied probability of default and this level could then be compared to the evolution of conservatism among IG names. Again, the relatively few names, which have active CDS markets on them poses a challenge.

More analysis could also be done on the theory of accounting quality proposed by Jorion et al (2008). They suggest that earnings management has caused a decline in the quality of accounting data, it would be interesting to see if this decline has continued, levelled off, or perhaps improved post-Financial crisis.

Finally, the approach of Baghai et al (2014) could also be extended out from 2007 to 2017 to see if there were any changes to how firms organize their capital structure in response to credit rating conservatism.

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Appendix

A.1: **Variable Descriptions**

Appendix 1

The table below shows a detailed explanation of the Compustat Codes used in calculating the financial metrics used in the multiple regressions.

Explanatory Variable	Definition	Compustat Codes
Book_Lev	Total Debt/Total Assets	(DLTT+DLC)/TA
ConvDe_TA	Convertible Debt/Total Assets	DCVT/AT
Rent_TA	Rent Payments/Total Assets	XRENT/AT
Cash_TA	Cash & Mkt Sec./Total Assets	CHE/AT
Debt_EBITDA	Total Debt/EBITDA	(DLTT+DLC)/EBITDA
NegDebt_EBITDA	1 if Debt_EBITDA < 0	Dummy Variable
IntCov	EBITDA/InterestPayments	EBITDA/XINT
Profit	EBITDA/Revenue	EBITDA/REVT
Size	Natural Log of Total Assets	Ln(AT)
Tangibility	PPE/Total Assets	PPEVEB/AT
CAPEX	CAPEX/Total Assets	CAPX/AT

A.2: **Data Pre-Processing**

I first download financial data and rating information from the WRDS databa se. To join these datasets, I use the field 'GVKey' as a unique common firm-level identifier. Once combined I then remove all GICS Sectors which are not in scope, leaving GICS 10 (Energy), 15 (Materials), 20 (Industrials), 25 (Consumer Discretionary), 30 (Consumer Staples), 35 (Health Care), 45 (Information Technology), 50 (Communication Services). This brings the total number of firm-year observations to 37,590.

I then generate the 11 Financial Metrics which will serve as the independent variables- the definitions and Computstat Codes can be seen in Appendix 1. Again, this follows the procedure of Baghai et al. (2014), however, I do not include profit volatility, Beta, and Idiosyncratic risk due to data unavailability.

For the 'Debt/EBITDA' metric, the intuition is that a high level of debt versus a low level of EBITDA, should be a taken as a negative in terms of credit rating (and vice versa). However, this would show firms that had a loss (negative value of EBIDTA), generating the 'lowest' values of 'Debt/EBITDA' and thus wrongly attributing this as a positive sign for their credit rating. This is rectified in two steps- first, negative values for Debt/EBITDA are floored at zero. Second, a dummy variable is created for 'Negative Debt/EBITDA', which applies a value of 1 for

firms with negative values, else 0 for firms with a positive value for 'Debt/EBITDA'.

To limit extreme outliers in the data, I winsorize[5] the independent variables. Profitability is winsorized at the 1st percentile (to eliminate a handful of extreme negative values). Interest Coverage, Leverage, Debt/EBITDA, Convertible Bonds, Rent, PPE, and CapEx variables are only winsorized to the 99th percentile as they only show extreme values at the upper bound.

The 'Size' variable is adjusted for inflation by converting the nominal values into real, 2005 US-dollar equivalency (Real Price = Nominal Price/CPI Adjustment). This is done using the US CPI index, creating an 'Inflation Adjustment' factor by dividing the CPI for each year by the base year and then applying that factor to the 'Size' variable. Following these steps, the data is ready to be analyzed.

A.3: **S&P Credit Rating Definitions**

S&P has the following ten broad ratings categories which they define as follows (Standard and Poor's, 2019):

- AAA, Investment Grade: extremely strong capacity to meet financial commitments.
- AA, Investment Grade: very strong capacity to meet financial commitments.
- A, Investment Grade: strong capacity to meet financial commitments, but somewhat susceptible to economic conditions and changes in circumstances.
- BBB, Investment Grade: adequate capacity to meet financial commitments, but more subject to adverse economic conditions.
- BB, Speculative Grade: less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions.
- B, Speculative Grade: more vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments.
- CCC, Speculative Grade: currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments.
- CC, Speculative Grade: highly vulnerable; default has not yet occurred but is expected to be a virtual certainty.
- C, Speculative Grade: currently highly vulnerable to non-payment, and ultimate recovery is expected to be lower than that of higher rated obligations.
- D, Speculative Grade: payment default on a financial commitment or breach of an imputed promise; also used when a bankruptcy petition has been filed.

[5] Winsorization is a statistical technique in which outliers are replaced with a chosen value; typically, the 99th percentile for high data points and 1st percentile for low data points.

A.4: **Financial Firms**

All the literature cited in this paper excludes 'Financials' from their analysis as financial firms typically have a different balance sheet composition compared to the broader universe of firms. Financial firms tend to take on higher leverage and invest less in 'Capex' or 'Property, Plant, and Equipment'. Despite these structural differences, I apply the previous methods to the sub-set financial firms (GICS Sector = 40) to see if there were any significant increases in conservatism from the pre-Lehman period to the period following the Lehman bankruptcy. I run an OLS regression with the financial sector firms with same dependent and independent variables and plot the resulting year-dummy variables.

The resulting coefficients of year dummy variables are presented in figure 10 below. We can see that although there does appear to be a general upward trend in the coefficients, due to the large standard errors (and resulting wide confidence intervals) we can not say that there is a statistically significant increase in conservatism. It could be that other financial-specific metrics (non-performing loans, interest rate spreads) could might provide more meaningful results.

Figure 10. Plot of coefficients of year dummies from Financial Sample OLS Regression

In the graph below I plot three series of year dummy coefficients over time for the sample containing only Financial firms. One for the overall sample of financial firms, a second for the Investment Grade subset of financial firms, and a third for the Speculative Grade subset of financial firms. Due to the width of the 95% confidence interval bands, for most of the sample we can not definitely say that there has been an increase in conservatism in credit rating

