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Three Essays on Opacity, Corporate Governance, and Credit Ratings

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THREE ESSAYS ON OPACITY, CORPORATE GOVERNANCE, AND CREDIT RATINGS

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
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ABSTRACT

In the first essay, utilizing a more recent and expanded 20-year sample 1991-2010 of dual-rated bonds issued, I confirm Morgan's (2002) finding that banks are relatively more opaque than nonbanks. The likelihood of a rating split is higher, and the magnitude of the rating gap is larger, for banks than nonbanks. Moreover, rating agency disagreements are more significant for banks with relatively higher loan and trading securities holdings and maintain lower capital, and for banks engaged in mortgage securitization. Importantly, I find that rating agency disagreements reflect market proxies of information uncertainty. Further, opacity makes external financing more costly. Equity returns surrounding new bond issues are significantly negative on average, and notably lower, when information uncertainty is higher and for banks compared to nonbanks.

In the second essay I investigate how corporate governance is related to bank opacity and how bank opacity is related to systematic and systemic risk. It is well known that opaque assets lead to higher systematic risk, which contributes to higher systemic risk. Banks by nature hold a large percentage of opaque assets, but the decision to hold such assets is partly endogenous. Results show that banks with relatively weak corporate governance hold a larger share of opaque assets. Consequently, they operate further along the risk-return frontier and have higher exposure to systemic risk. At the margin, strong corporate governance at publicly traded U.S. banking organizations reduces financial instability.

In the third essay I examine if the rating agencies sacrifice the rating timeliness for the sake of rating stability. Credit rating agencies argue that markets expect them to issue stable ratings. Examining equity market reactions around CreditWatch events in 2002-2005, I find that the pursuit of stable rating may have reduced the timeliness of rating changes. Abnormal equity

returns of a firm prior to being listed on CreditWatch are effective predictors of the ultimate change in rating that occurs when the firm is delisted. Equity markets exhibit no reaction when a firm is delisted from CreditWatch, suggesting information about the rating change is already reflected in equity prices at the time of delisting.

This dissertation is approved for recommendation
to the Graduate Council.

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DEDICATION

I would like to dedicate the dissertation to my mentors and my parents.

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Introduction

The dissertation is inspired by the recent financial crisis, focusing primarily on bank opacity, corporate governance, and credit ratings. First, utilizing a more recent and expanded 20-year sample 1991-2010 of dual-rated bonds issued, I find that banks are relatively more opaque than other industries. Moreover, I find that rating agency disagreements reflect market proxies of information uncertainty as captured by analyst coverage, standard deviation and absolute error of analyst earnings forecasts, trading volume and bid-ask spreads. Further, opacity increases the informational asymmetry between insiders and outsiders, and makes external financing more costly.

The process of how systemic risks occur is a very interesting question. The second essay addresses the question of how corporate governance plays a role in banks' systemic risks through managers' choices of bank assets. The results suggest that corporate governance, such as managerial incentives, ownership, and board structures, influence banks' choices of opaque assets, and that opaque assets held by banks lead to more systematic risk for investors and more systemic risk for society.

In the third essay, I examine the issue of timeliness when rating agencies announce the potential default risk. Rating agencies on one hand are expected by the market to convey long-term, permanent, and structural changes of firms' default risk and thus only to make rating changes when a reversal in rating changes in the near future is unlikely. On the other hand, rating agencies are expected to convey information about the default risk of firms to the market in a timely fashion so that investors can use the timely information in pricing securities prices. The results suggest rating agencies sacrifice rating timeliness for the sake of rating stability.

Are Banks Really Opaque: Evidence from 1991-2010

A. Introduction

The informational asymmetry between borrowers and lenders is a primary reason for the existence of financial intermediaries (Leland and Pyle, 1977). Banks are delegated monitors for outside capital (Diamond, 1984) and provide liquidity for demand deposits (Diamond and Dybvig, 1983). The nature of its lending activities as well as the moral hazard of deposit insurance, which distinguish banks from nonbanks, also make banks opaque.

Opacity is the information uncertainty that even the most sophisticated investors face in accurately assessing the fundamental value of a firm that arises from insufficient disclosure or inherent complexity of firms. Because it is difficult for the market to assess the intrinsic value of banks, the problems of "sick" banks will infect "healthy" banks, which can provoke self-fulfilling large bank failures (Diamond and Dybvig, 1983). The limitations to informed arbitrage and threat of insolvency associated with opacity contributes to systemic risk and the fragility of the real economy. Governmental regulation and supervision are necessary because market discipline may be ineffective when banks are opaque.

The adverse selection and moral hazard problems associated with information asymmetry make external financing costly for firms (Myers and Majluf, 1984).Relative to equity, debt financing is least costly for the uninformed investor. Collateralization and the fixed payoff of debt minimize the private information advantage of insiders about future cash flows. Moreover, the discipline of interest and principal repayments, debt covenants, and monitoring by independent third parties (credit rating agencies) constrain the agency costs of excess cash flow. Firms have a strong incentive to issue debt because the value of debt is least sensitive *ex ante* to public signals.[1] But debt is risky *ex post*. A sufficiently bad aggregate economic shock that reduces the value of collateral and the adequacy of capital can make debt information sensitive, and thereby, trigger systemic risk (Dang, Gorton, and Holmström, 2009).

In this study we use new debt issues by publicly traded firms over the 20-year period 1991–2010 as the market event for examining the economic impact of information uncertainty. And as in Morgan (2002), that spans an earlier decade 1983-1993, rating agency disagreements between Moody's and Standard & Poor's are used to proxy for information uncertainty. We confirm that banks are still relatively more opaque than nonbanks. Rating splits are more likely, and the magnitudes of rating gaps are larger, for banks than for firms in other industries. Moreover, rating agency disagreements are more significant for banks, with relatively higher loan and trading securities holdings and lower capital, and that participated in mortgage securitization activities. The deregulation of the banking industry, which intensified competition and reduced the discipline of charter value, also contributed to increased information uncertainty about banks. Recognizing that only comparatively high quality debt could be issued during the 2008 financial crisis, the pattern of rating disagreements pre-crisis and post-crisis suggests that the quality of bank debt issues improved in the years leading up to 2008 and remained relatively high subsequently.

Using market proxies for information uncertainty, this study also revisits Flannery, Kwan, and Nimalendran's(2004), which spans the period 1990-1997,and argues that banks are not opaque but simply boring. In contrast to Flannery, Kwan, and Nimalendran(2004), we find that rating agency disagreements are more likely when: analyst coverage is limited; the dispersion of

[1]Moreover, faced with the choice of public or private (bank) debt, firms will choose private debt when the rigidity of bond covenants exceeds the agency cost of monitoring (Berlin and Loeys, 1988).

analyst earnings are high, and accuracy of analyst earnings, are low; bid-ask spreads are high; and trading volume is low. These findings corroborate Livingston, Naranjo, and Zhou (2007) that ratings disagreements imbed market proxies of information uncertainty.

Last but not least, we show that opacity makes external financing by firms more costly. Equity returns surrounding new debt issues are significantly negative on average, and more negative, when information uncertainties about firms, captured either through rating agency disagreements or market proxies, are high. Moreover, controlling for market proxies of information uncertainty, equity returns surrounding new debt issues by banks are significantly more negative compared to nonbanks when rating agency disagreements are more substantial. These results are consistent with Livingston and Zhou's (2010) finding that yield spreads are higher for new debt issues that are split-rated, and increase, with the magnitude of the rating gap.

The paper is organized as follows. Section 2 describes the research design. Empirical results are presented and discussed in Section 3. Section 4 concludes.

B. Empirical Design

B.1 Research Questions

This study examines three distinct but related issues. First, has the information uncertainty of banks relative to nonbanks changed in the recent two decades 1991-2010 compared to the decade prior? The sample period covers three major deregulatory events – the demise of "too big to fail" after 1986, the Interstate Banking and Branching Efficiency Act of 1994, and the Gramm-Leach-Bliley Act of 1998, as well the financial crisis of 2008.Moreover, is the information uncertainty for banks related to its asset composition, securitization activities, and capital? Second, are market proxies of information asymmetry and credit ratings disagreements consistent and complementary indicators of information uncertainty? Third, do equity markets price information uncertainty?

B.2 Information Uncertainty

New issues of debt by publicly traded firms are used as the natural market experiment for examining information uncertainty. Issue data was obtained from Thomson Financial over the 20-year period January 1991 through December 2010 covered in its SDC Platinum Global New Issues database. As in Cantor and Packer (1996), new debt issues under $10 million and less than one year of maturity are excluded, as are issues with significant equity features, equipment trusts, collateralized mortgage obligations, government guaranteed issues, variable rate issues, ESOP, lease certificates, and foreign issues. Further, as in Morgan (2002), new debt is restricted to issues rated both by the two major rating agencies, Moody's and Standard & Poor's. The reasoning is simply that rating agencies in the business of assessing risk will disagree more when information uncertainty about the issuer is high.

Bond maturity is the number of years between issue and maturity dates, and face value, is expressed in denominations of $10 million. As detailed in Appendix A, letter ratings by the two agencies are mapped into a single numeric scale, with better credit quality indicated by lower numbers: AAA = Aaa = 1, AA+ = Aal =2,…,C = C = 21.Issuers are also classified into ten industries as in Morgan (2002). Firms with SIC codes of 6021, 6022, 6029, 6712, or 6719 are classified as banks, and the SIC codes used to construct the nine other industries are detailed in Appendix B.

Average Rating is the mean of Moody's and S&P numerical ratings with higher values indicating higher risk. Variances in ratings across and within issuers are depicted separately. Standard deviation in ratings *between* is the average standard deviation across issues in the same industry, and standard deviation in ratings *within*, is the average standard deviation across issues by the same issuer. Smaller variances between firms suggest a central tendency in rating distributions, and larger variances within firms, imply higher ratings ambiguity.

Rating gaps as well as rating splits describe rating agency disagreements. Rating gap is the absolute difference between Moody's and S&P ratings, and information uncertainty about a firm's true risks will, *ex post*, cause rating agencies to underrate some relatively safe and overrate some relatively risky bonds. *Kappa* is a statistical measure of inter-rater reliability that takes into account that agreement can occur by chance, and is defined as $[P_0 - P_e]/[100 - P_e]$, where P_0 is the percentage of same-rated bonds observed and P_e is the expected percentage given the distribution of ratings. *Kappa* equals1, if the raters are in complete agreement, and equals 0, if there is no agreement among the raters.

This study's sample over the more recent 20-year period January 1, 1991 through December 31, 2010, contains 25,652 new bond issues by 2,505 unique firms, of which, 3,868 are issued by 164 unique banks. Table 1 reports summary statistics on issue and issuer characteristics both for the overall sample period as well as for two non-overlapping 10-year sub-periods compared to Morgan's (2002) sample over an earlier ten-and-a-half year period January 1983 to July 1993. Note that in this study's sample:(*i*) the average annual number of issues and number of issues per issuer is higher; (*ii*) the average issue size is larger; and (*iii*) the average issue maturities are shorter. Moreover, contrasting the most recent decade with the decade prior, average face value are almost five-times higher and average maturities about fifty percent longer, for bonds issued by banks compared to non-banks. But the distributions of issues across industries, as well as average ratings and standard deviation of ratings, are similar.

Debt issues by banks are better rated on average quality, by almost two notches, compared to debt issues by firms in other industries. The between variance on bank issues is only half that

Table 1: Ratings and New Bond Issue Characteristics by Issuer Type

Summary statistics covers 25,652 new bonds issued from 1991 through 2010. Issues/Issuers stand for the total number of bond issues and unique bond issuers across industries. Letter ratings by the two agencies are transformed into a numeric scale and better letter ratings correspond to lower numbers. [a]Average Rating is the average of Moody's and S&P ratings. [b]Standard Deviation in Ratings Between and Within are the average standard deviations across issues in the same industry and across issues by the same issuer, respectively. [c]All Other refers to agriculture, forestry, fishing, and construction. Numeric ratings and SIC codes used to classify industries are detailed in Appendices A and B.

Morgan (2002) Sample: 1983-1993 Issuer Type	Issues /Issuers	Average Rating[a]	Standard Deviation in Ratings Between[b]	 Within[b]	Average Maturity (years)	Average Face Value ($millions)
Bank	848/220	5.29	2.98	1.20	8.40	158.80
Other	7,014/2,410	7.14	5.48	0.94	13.50	176.80
Manufacturing	1,858/661	8.52	4.49	1.03	14.20	201.00
Mining	107/43	10.92	3.13	0.74	14.30	172.90
Trade	511/217	10.08	3.86	1.05	14.70	147.60
Services	341/161	10.72	3.34	1.37	12.80	125.50
Transportation	182/63	9.41	4.11	1.26	15.30	165.40
Public utilities	1,884/360	6.93	3.89	0.86	19.10	133.70
Insurance	150/59	6.23	4.31	0.83	14.00	138.10
Other Finance and Real Estate	1,941/810	4.15	3.19	0.80	6.60	217.30
All Other[c]	40/29	12.36	3.65	0.42	11.20	131.90
New Sample: 1991-2010 **Issuer Type**	**Issues /Issuers**	**Average Rating**	**Standard Deviation in Ratings** **Between**	 **Within**	**Average Maturity (years)**	**Average Face Value ($millions)**
Bank	3,868/146	5.25	1.69	0.72	6.12	321.03
Other	21,784/2,359	8.61	3.39	0.84	10.19	280.17
Manufacturing	4,157/761	8.16	3.76	0.90	10.44	312.24
Mining	760/196	10.77	3.68	0.68	11.53	321.63
Trade	1,120/218	8.70	4.08	0.97	11.12	312.54
Services	1,341/313	9.97	4.02	0.75	7.98	318.54
Transportation	507/67	8.59	3.66	0.97	12.77	284.55
Public utilities	2,890/405	8.42	3.61	1.18	12.95	214.19
Insurance	687/127	8.64	3.67	0.87	12.73	296.89
Other Finance and Real Estate	10,051/226	5.01	2.62	0.49	4.89	236.34
All Other	271/46	11.45	2.49	0.97	8.77	179.51
Subsample: 1991-2000						
Bank	2,369/110	5.70	1.61	0.72	5.44	127.11
Other	12,540/1,634	8.26	3.24	0.58	10.46	163.88
Manufacturing	2,287/540	7.69	3.57	0.55	11.01	177.15
Mining	370/118	9.89	3.63	0.56	12.87	169.74
Trade	635/155	8.11	3.77	0.60	11.99	182.55
Services	769/191	9.10	3.80	0.45	7.32	180.08
Transportation	317/51	8.50	3.06	1.01	14.19	150.99
Public utilities	1,702/291	8.07	3.66	0.52	12.87	202.12
Insurance	276/86	6.35	2.43	0.49	11.13	174.41
Other Finance and Real Estate	6,072/167	5.17	2.49	0.34	4.31	116.91
All Other	112/35	11.42	2.70	0.70	8.47	121.00
Subsample: 2001-2010						
Bank	1,499/69	4.54	1.55	0.59	7.18	627.51
Other	9,244/1,392	9.03	3.51	0.79	9.82	417.35
Manufacturing	1,870/472	8.72	3.91	0.74	9.75	477.45
Mining	390/115	11.59	3.53	0.60	10.27	465.73
Trade	485/117	9.46	4.35	0.73	9.99	482.73
Services	572/185	11.13	4.02	0.68	8.87	504.68
Transportation	190/35	8.29	4.38	1.21	10.87	319.62
Public utilities	1,188/238	9.45	3.53	0.91	12.53	432.66
Insurance	411/73	6.38	2.70	0.70	11.41	433.96
Other Finance and Real Estate	3,979/130	4.77	2.79	0.47	5.77	418.59
All Other	159/27	11.47	2.34	1.03	8.98	220.72

on nonbank issues, which suggests that ratings on bank debt tend to cluster around the mean. The within variance is, however, higher for bank issues, which indicates that individual bank risks change more over time. Contrasting the most recent decade with the decade prior, ratings for bank compared to non-bank debt issues improved by more than one notch and within standard deviation in ratings decreased by almost twenty percent.

Table 2 reports unconditional measures of rater disagreement across industries. Debt issues by banks have the highest average credit quality, followed closely by companies in other finance and real estate as well as in insurance. But there is considerably greater information uncertainty about the risk of banks.

The gap between the mean ratings by Moody's and S&P is more than fifty percent higher for bank issues than for the typical nonbank issue. The rank correlation between ratings across issues within the same industry, though high in all industries, is lowest for banks. The average *Kappa* statistic, which reflects the degree of agreement between rater, is lowest for banks. The relatively high average *Kappa* for finance and other real estate is predictable since these issues tend to be backed by a pool of specific, homogenous assets 'locked' up in special purpose vehicles that reduce the risk of asset substitution. The average *Kappa* is highest for issues by mining companies, which is surprising since industry cash flows are notably risky, but perhaps less subject to managerial misappropriation because of stringent regulation.

Rating splits are considerably more frequent for banks and insurance companies, and least frequent, for other finance and real estate. The pattern of splits also shows that when a split occurs, the likelihood of a one-notch rating gap is relatively the same across industries except for other finance and real estate. However, compared to other industries, a rating gap of one or more notches is most likely in split rated debt issued by banks and insurance companies.

Table 2: Rating Agency Disagreements over New Bond Issues by Sector

Table reports various measures of disagreement between raters. [a]Correlation is the rank correlation in ratings across firms in the same industry between issuers. [b]*Kappa* statistics are defined as $[P_0 - P_e]/[100 - P_e]$,where P_0 is the percentage of similar-rated bonds observed, and P_e is the expected percentage given the distribution of ratings. As a measure of inter-rater reliability, a *Kappa* value equal to 0 represents complete disagreement, and to 1, complete agreement. [c]Absolute gap is the absolute value of the rating split between Moody's and S&P. [c]Ratings gap distributions are the percentages expressed relative to the number of split-rated issues. [e]All Other refers to agriculture, forestry, fishing, and construction. Numeric ratings and SIC codes used to classify industries are detailed in Appendices A and B.

Morgan (2002) Sample: 1983-1993						**Return Gap Distribution[d] (percentage)**		
Issuer Type	**Average Ratings Moody's/S&P**	**Correlation between Ratings[a]**	**Kappa Statistics[b]**	**Moody's ≠ S&P (% of issues)**	**Average Absolute Gap[c]**	**Gap=1**	**Gap=2**	**Gap=3**
Bank	5.5/5.1	0.91	0.30	62.9	0.83	44.81	15.57	2.48
Other	7.2/7.1	0.97	0.45	50.0	0.65	38.80	9.27	2.67
Manufacturing	8.5/8.6	0.97	0.39	56.3	0.74	42.30	10.76	3.22
Mining	11.1/10.8	0.95	0.23	71.0	0.93	50.47	18.69	1.86
Trade	10.1/10.1	0.97	0.30	63.6	0.81	48.92	11.74	2.94
Services	10.7/10.7	0.97	0.38	56.3	0.68	45.75	9.68	0.88
Transportation	9.6/9.2	0.95	0.37	57.1	0.76	42.31	10.44	4.40
Public Utilities	6.9/7.0	0.96	0.45	50.1	0.62	40.34	7.75	2.02
Insurance	6.7/5.8	0.94	0.09	81.3	1.33	44.67	22.00	14.67
Other Finance and Real Estate	4.2/4.1	0.96	0.57	34.8	0.46	25.81	7.01	1.95
All Other[e]	12.5/12.2	0.96	0.30	60.0	0.73	50.00	7.50	2.50

New Sample: 1991-2010						**Return Gap Distribution (percentage)**		
Issuer Type	**Average Ratings Moody's/S&P**	**Correlation between Ratings**	**Kappa Statistics**	**Moody's ≠ S&P (% of issues)**	**Average Absolute Gap**	**Gap=1**	**Gap=2**	**Gap=3**
Bank	4.96/5.54	0.82	0.22	65.2	0.94	40.33	22.08	2.76
Other	8.69/8.53	0.95	0.52	45.6	0.60	35.64	6.93	2.68
Manufacturing	8.24/8.07	0.97	0.50	45.9	0.57	37.31	6.69	1.92
Mining	10.88/10.66	0.97	0.71	47.4	0.61	37.24	8.42	1.71
Trade	8.71/8.69	0.97	0.44	51.6	0.64	43.48	4.64	3.49
Services	10.08/9.86	0.98	0.46	48.8	0.59	41.09	6.34	1.41
Transportation	8.53/8.30	0.90	0.48	48.9	0.74	33.93	8.09	4.13
Public utilities	8.69/8.58	0.96	0.46	49.5	0.65	39.24	7.54	2.67
Insurance	6.63/6.10	0.93	0.42	50.8	0.72	34.21	12.23	4.37
Other Finance and Real Estate	5.00/5.02	0.96	0.66	28.4	0.36	22.18	4.76	1.45

Subsample: 1991-2000 Issuer Type	Average Ratings Moody's/S&P	Correlation between Ratings	Kappa Statistics	Moody's ≠ S&P (% of issues)	Average Absolute Gap	Return Gap Distribution (percentage)		
						Gap=1	Gap=2	Gap=3
Bank	5.6/5.9	0.80	0.37	56.2	0.79	38.37	14.61	3.25
Other	8.3/8.2	0.95	0.47	46.9	0.62	37.33	6.18	3.24
Manufacturing	7.8/7.6	0.97	0.49	45.2	0.55	38.92	4.20	2.09
Mining	10.0/9.8	0.97	0.48	47.8	0.59	38.92	7.84	1.08
Trade	8.0/8.2	0.96	0.41	53.4	0.70	44.88	2.68	5.83
Services	9.2/9.0	0.97	0.45	49.0	0.59	41.61	5.59	1.82
Transportation	8.5/8.5	0.95	0.45	47.9	0.62	37.54	7.89	2.52
Public Utilities	8.1/8.0	0.95	0.43	51.3	0.69	40.72	7.2	3.37
Insurance	6.7/6.0	0.92	0.36	55.8	0.82	36.59	13.41	5.79
Other Finance and Real Estate	5.2/5.1	0.95	0.65	27.3	0.37	19.96	5.62	1.68
All Other[c]	11.3/11.5	0.89	0.47	44.6	0.66	37.50	2.68	4.47

Subsample: 2001-2010 Issuer Type	Average Ratings Moody's/S&P	Correlation between Ratings	Kappa Statistics	Moody's ≠ S&P (% of issues)	Average Absolute Gap	Return Gap Distribution (percentage)		
						Gap=1	Gap=2	Gap=3
Bank	4.01/5.06	0.84	0.05	79.3	1.18	43.43	33.89	1.99
Other	9.14/8.92	0.95	0.51	43.7	0.60	33.83	7.65	2.26
Manufacturing	8.83/8.61	0.97	0.49	46.8	0.61	35.35	9.73	1.71
Mining	11.74/11.45	0.97	0.49	46.9	0.62	35.64	8.97	2.31
Trade	9.59/9.33	0.98	0.46	49.3	0.57	41.65	7.22	0.41
Services	11.24/11.03	0.98	0.47	48.6	0.58	40.38	7.34	0.87
Transportation	8.57/8.01	0.87	0.51	43.1	0.93	27.89	8.42	6.85
Public utilities	9.48/9.41	0.96	0.48	46.8	0.60	37.12	7.91	1.77
Insurance	6.60/6.16	0.94	0.46	47.5	0.66	32.60	11.44	3.40
Other Finance and Real Estate	4.70/4.84	0.97	0.64	30.1	0.36	25.56	3.44	1.10
All Other[c]	11.48/11.45	0.95	0.60	34.6	0.43	28.30	4.40	1.89

Between the recent and preceding decade, assessments of industry risk by rating agencies remained relatively unchanged except for banks. Between decades, the average rating on bank debt was about a notch higher and the rank correlation of ratings on bank debt was similar. *Kappa* statistics show, however, that ratings agreement on bank debt issues fell to almost zero in the recent decade. Between decades, the rating split frequency of bank debt increased from 56.2% to 79.3%, the absolute rating gap from 0.79 to 1.18, and the likelihood of a rating gap of one or more from 56.23% to 79.31%.

B.3 Market Proxies for Information Uncertainty

This study, which explores whether rating agency disagreements mirror market proxies of information uncertainty, extends Morgan (2002). Flannery, Kwan, and Nimalendran (2004) argue that if banks are relatively more opaque than nonbanks, equity markets will imbed more divergent opinions about the future earnings and stock prices of banks. In particular, the dispersion and accuracy of analysts' earnings forecasts, bid-ask spreads, trading volumes, and return volatilities will reflect information uncertainty. In a cross-sectional analysis over the period 1990-1997, Flannery, Kwan, and Nimalendran (2004) find no statistically significant difference between banks and other industries. The quoted bids-ask spreads, effective spreads, and adverse selection component of bid-ask spreads are very similar between banks and nonbanks and across large NYSE-traded and small NASDAQ-traded banks. NASDAQ-traded banks appear to have lower trading volumes compared to nonbanks, and analysts' forecasts of earnings, to be more accurate for banks.

These findings differ from extant literature. Using intraday stock transactions data, Brennan and Subrahmanyam (1995) show that a larger analyst following tends to reduce information asymmetry. Desai, Nimalendran, and Venkataraman (1998) find significant changes in trading activity, volatility, and adverse information component of the bid-ask spread following a stock split. Livingston, Naranjo, and Zhou (2007) show that rating splits are more likely for firms with higher adverse information component in the bid-ask spread, higher standard deviation of analyst earnings forecasts and absolute forecast errors, and smaller analyst coverage. And in a subsequent paper, Flannery, Kwan, and Nimalendran (2010) note that a dramatic shift in the equity trading characteristics of bank stocks during the 2007 financial crisis is consistent with increased information uncertainty.

As in Flannery, Kwan, and Nimalendran (2004), we use the bid-ask spread as a percentage of share price, trading volume, number of stock analysts, standard deviation of quarterly analyst earnings (EPS) forecasts, and error of quarterly analyst earnings (EPS) forecasts computed as the absolute difference between actual and forecasted quarterly earnings (EPS), as proxies for information uncertainty. Data on the bid-ask spread and trading volume – the daily number of shares of stock traded, are obtained from the CRSP database, and earnings (EPS), from the Thomson Reuters I/B/E/S database each quarter. These datasets are merged together with debt issues by firm ID. The merger of data from FR Y-9C, CRSP, and IBES results in 115 unique banks.

Further, this study examines equity market reactions to the issue of new debt by firms. Myers and Majluf (1984) show that information asymmetry between insiders and outside investors make external financing by firms costly. Using a probability of information-based trading (PIN) measure from a sequential trading model for stocks, Easley, Hvidkjaer, and O'Hara (2002) show that information risk is a determinant of asset returns. Jones, Lee, and Yeager (2009, 2010) find that after controlling profitability, banks with more opaque investments have higher costs of capital, and opaque banks, which benefited the most from merger induced intraindustry revaluations in the pre-crisis period, also lost the most in the post-crisis period.

Similarly, Livingston and Zhou (2010) find that investors require an information uncertainty yield premium for split-rated bonds, and Liu and Moore (1987), that the magnitude of the bond price reaction to a split rating is greater for lower rated debt. Lastly, Peristiani, Morgan, and Savino (2010) show that equity markets largely deciphered on its own which banks would encounter difficulties in financing long before the stress test results were revealed, and banks with larger capital gaps experienced more negative abnormal returns.

Because the issue of dual rated new debt is widely known both to rating agencies and potential investors prior to issue date, a 62-day window (-60,+1) starting 60 days before issue date and one day post issue data is used to compute an annualized cumulative abnormal return as the difference the daily and CRSP equal-weighted index returns. An annualized standard deviation of daily returns over the same event window is also calculated.[2]

Table 3 reports summary statistics for the above variables. Bid-ask spread and trading volume of banks and nonbanks are similar. Banks have the largest number of analysts with average of 15, and together with insurance companies, the highest analyst forecast errors among industries.

B.4 Information Uncertainty of Banks

Morgan (2002) contends that the information uncertainty of banks is inevitable because of the unique nature of bank assets (loans and trading assets in particular)in conjunction with high leverage, and Gorton (2010),that the asset complexities of MBS activities worsen information asymmetry. Our sample of banks consists of publicly traded U.S. bank or financial holding companies (BHCs) that had the requisite market and financial statement data over the sample

[2]Various event windows of (0,0), (-1,+1), (-15,+1), and (-30,+1) and value-weighted CRSP index return were also used. Results are similar.

period 1991-2010. In addition to the financial crisis in 2008, the sample period covers three major deregulatory events – the demise of "too big to fail" after 1986, the Interstate Banking and Branching Efficiency Act of 1994, and the Gramm-Leach-Bliley Act of 1998.[3,4]

We refer to bank entities either as "banks" or "BHCs". Consolidated financial statement data for BHCs' are obtained from the Federal Reserve Board FR Y-9C reports. A bank with missing or unavailable data was excluded for that quarter, resulting in a sample of 3,464 bank-quarter observations and 124 unique banks.[5]

Bank assets are classified into seven major categories as in Morgan (2002).[6] Cash and federal funds, as well as premises and intangibles, have the least valuation uncertainty and are relatively more transparent than loans and trading assets. Premises and Intangible Assets, which are relatively small proportions of bank assets, represent tangible fixed assets and goodwill and other nonmonetary intangible assets, respectively.[7]

Loans, as well as securities and trading assets, are the primary sources of opacity. Loans include commercial real estate loans, residential real estate loans, and all other loans. Other opaque assets consists of: (*i*) mortgage-backed securities, including those not guaranteed by GNMA and those not issued by FNMA and FHLMC; and (*ii*) asset-backed securities, which includes credit

[3]The interstate restrictions of the Bank Holding Company act were repealed by the Interstate Banking and Branching Efficiency Act in 1994, which allowed interstate mergers between adequately capitalized and managed banks, subject to concentration limits, state laws, and Community Reinvestment Act.

[4]Gramm-Leach-Bliley Act enacted November 1999, repealed part of the Glass-Steagall Act of 1933, which allowed commercial and investment banks to consolidate. Nobel Prize-winning economists Paul Krugman called Senator Phil Gramm "the father of the financial crisis" because of his sponsorship of the Act, and Joseph Stiglitz, that the Act helped to create the crisis.

[5]There are 121 unique banks after merging banking financial data with IBES dataset and 115 banks after merging bank financial data with CRSP dataset for stock return values.

[6]Morgan (2002) divides bank assets into cash, federal funds, loans, trading assets, premises, intangibles, and other assets.

[7]For example, mortgage servicing assets, purchased credit card relationships and nonmortgage servicing assets, and other identifiable intangible assets

Table 3: Market Proxies of Information Uncertainty

Table provides summary statistics for market proxies of information uncertainty. Numbers of analysts are the total numbers that cover a stock. Standard deviations of EPS forecasts are dispersions of quarterly earnings forecast. Absolute error of EPS forecasts is the absolute difference between actual and forecasted quarterly EPS. BAS/PRC is the bid-ask spread divided by price. Trading volume is the daily number of equity shares traded in millions. Holding Period Returns are annualized cumulative abnormal returns around a 62-day window (-60,+1) computed as the difference between daily and CRSP equal-weighted index returns, and annualized standard deviation, computed from daily returns (-60,+1).

	Number of Unique Firms	Mean	25^{th} Percentile	Median	75th Percentile	Standard Deviation
Number of Analysts						
Banks	121	15.011	11	15	19	5.883
Manufacturing	607	9.994	6	10	13	5.427
Mining	163	10.817	5	9	16	7.363
Trade	165	11.959	6	13	17	6.523
Services	237	10.428	4	9	16	6.950
Transportation	53	8.941	6	8	13	4.367
Public Utilities	303	6.398	2	4	9	5.969
Insurance	110	9.918	5	11	15	5.839
Other Finance & Real Estate	158	8.093	4	7	12	5.075
All Other	39	7.762	4	8	11	4.266
Standard Deviation of Analyst EPS Forecasts						
Banks	121	0.042	0.010	0.020	0.040	0.064
Manufacturing	607	0.042	0.010	0.020	0.040	0.088
Mining	163	0.081	0.030	0.050	0.100	0.090
Trade	165	0.027	0.010	0.010	0.030	0.043
Services	237	0.025	0.010	0.020	0.030	0.030
Transportation	53	0.081	0.020	0.030	0.070	0.129
Public Utilities	303	0.153	0.020	0.030	0.060	3.168
Insurance	110	0.310	0.010	0.020	0.060	1.543
Other Finance & Real Estate	158	0.079	0.020	0.050	0.090	0.129
All Other	39	0.049	0.010	0.030	0.060	0.061
Absolute Error of Analyst EPS Forecasts						
Banks	121	0.346	0.010	0.040	0.120	0.376
Manufacturing	607	0.164	0.010	0.040	0.120	0.424
Mining	163	0.226	0.037	0.100	0.270	0.269
Trade	165	0.099	0.010	0.030	0.080	0.206
Services	237	0.059	0.010	0.030	0.075	0.123
Transportation	53	0.153	0.020	0.060	0.140	0.383
Public Utilities	303	0.018	0.007	0.023	0.023	6.139
Insurance	110	4.282	0.020	0.070	0.290	2.584
Other Finance & Real Estate	158	0.365	0.050	0.166	0.373	0.776
All Other	39	0.214	0.020	0.068	0.185	0.175
Bid-Ask Spread/Price						
Banks	115	0.023	0.016	0.020	0.026	0.011
Manufacturing	597	0.025	0.017	0.022	0.030	0.013
Mining	157	0.030	0.019	0.027	0.038	0.015
Trade	169	0.024	0.017	0.022	0.028	0.011
Services	243	0.027	0.018	0.023	0.033	0.016
Transportation	53	0.024	0.017	0.022	0.029	0.012
Public Utilities	290	0.024	0.013	0.019	0.028	0.021
Insurance	72	0.021	0.014	0.018	0.024	0.011
Other Finance & Real Estate	179	0.026	0.017	0.023	0.030	0.013
All Other	41	0.032	0.024	0.029	0.037	0.014
Trading Volume						
Banks	115	1.585	0.387	0.849	1.858	0.003
Manufacturing	597	2.200	0.221	0.647	1.899	0.005
Mining	157	1.521	0.161	0.505	1.510	0.003
Trade	169	2.444	0.235	0.759	2.603	0.004

	Number of Unique Firms	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
Services	243	2.297	0.090	0.400	1.423	0.007
Transportation	53	0.860	0.179	0.400	0.897	0.001
Public Utilities	290	1.402	0.076	0.226	0.847	0.004
Insurance	72	4.685	0.076	0.422	2.136	0.032
Other Finance & Real Estate	179	1.866	0.332	0.839	2.727	0.003
All Other	41	0.661	0.085	0.291	0.926	0.001

	Number of Unique Firms	**Mean**	**25th Percentile**	**Median**	**75th Percentile**	**Standard Deviation**
Annualized Holding Period Returns Around Issue Date (-60,+1)						
Banks	115	-0.065	-1.027	-0.155	-0.155	1.835
Manufacturing	597	-0.066	-1.162	-0.132	-0.132	2.469
Mining	157	-0.002	-1.223	-0.037	-0.037	2.490
Trade	169	-0.129	-1.152	-0.197	-0.197	2.115
Services	243	0.121	-0.995	0.007	0.007	2.236
Transportation	53	-0.089	-1.093	-0.309	-0.309	1.957
Public Utilities	290	-0.063	-1.144	-0.195	-0.195	2.270
Insurance	102	-0.048	-1.100	-0.026	-0.026	1.980
Other Finance & Real Estate	179	0.054	-0.975	-0.059	-0.059	2.003
All Other	41	0.374	-0.911	0.274	0.274	2.101
Standard Deviation of Daily Returns Prior to Issue Date						
Banks	115	0.296	0.209	0.267	0.267	0.145
Manufacturing	597	0.332	0.218	0.282	0.282	0.181
Mining	157	0.391	0.252	0.336	0.336	0.205
Trade	169	0.320	0.228	0.280	0.280	0.159
Services	243	0.372	0.238	0.320	0.320	0.204
Transportation	53	0.323	0.237	0.297	0.297	0.130
Public Utilities	290	0.308	0.158	0.224	0.224	0.293
Insurance	102	0.286	0.184	0.258	0.258	0.164
Other Finance & Real Estate	179	0.342	0.224	0.306	0.306	0.172
All Other	41	0.435	0.316	0.379	0.379	0.193

card receivables, home equity lines, automobile loans, other consumer loans, commercial and industrial loans. Securities are financial assets purchased for the long term that are either held-to-maturity or available-for-sale. Financial securities held-to-maturity is reported at amortized cost and no adjustments are made for transitory fluctuations in fair value of these securities. Available-for-sale securities are reported at fair value and changes in fair value are not accounted as changes in net income but charged or credited directly to equity. In contrast, trading assets, which are concentrated primarily in large banks, are debt and equity securities bought and sold in the near term. Like securities, trading assets are also reported at fair value, but changes in fair value are recorded as changes in net income.

Lastly, total assets and square of total assets, which proxy for bank size, are inflation-adjusted using the annual Consumer Price Index (CPI). Capital, which proxies for bank equity, is computed as the ratio of total equity to risk-weighted total assets using the method specified under the 1989 Basel Accord for determining minimum bank capital requirements.[8]

Table 4 reports the bank holding company assets prior to new bond issuance. Statistics are calculated for 3,464 bank observations over 80 quarters for new bond issues. With a mean value of $207.11 million, loans represent almost half of bank's total assets. Trading assets and securities, cash, intangible assets, and federal funds make up the remaining of bank assets. Fixed assets, by contrast, make up less than one percent of assets. Trading assets have a wide range of

[8]The U.S. adopted the capital requirement standards established by the Bank for International Settlements (BIS) in Basel, Switzerland in 1989. Minimum capital is specified as a percentage of the risk-weighted assets of the bank. The weight is zero for U.S. Treasury securities and mortgage-backed securities directly guaranteed by the Government National Mortgage Association (Ginnie Mae); 20 percent for general obligation municipal bonds and mortgage-backed securities guaranteed by the Federal National Mortgage Association (Fannie Mae) or the Federal Home Loan Mortgage Corporation (Freddie Mac); 50 percent for municipal revenue bonds and privately issued mortgage-backed securities; and 100 percent in business and consumer loans. Total capital must be at least 8% of total risk-weighted assets.

values ranging from 1,699 to 63,416. Capital ratios improved over the last two decades because of compliance with the Basel Accord. The average risk weighted capital ratio is 9.19%and the median is 8.82%.

C. Empirical Results

C.1 Information Uncertainty across Industries

Morgan (2002) finds that banks are relatively more opaque than other industries sectors during 1983 to 1993. Using market microstructure variables from 1990-1997 as proxies for opacity, Flannery, Kwan, and Nimalendran (2004) find, however, that banks are not significantly opaque, just boring. To examine whether banking industries are more opaque than all other industries, we run logit and probit regressions of rating disagreements on issuer type controlling for issue characteristics. A rating split dummy variable and absolute rating gaps are used as substitutes for rating disagreement. Logit and ordered probit egression results are reported in Table 5. Issuer type is a dummy variable. Issue characteristics are average rating, maturity, face value, and standard deviation of rating gap.

Results in Table 5 confirm Morgan (2002). The likelihood of a rating split is higher, and the magnitude of the absolute rating gap is larger, for banks than non-banks. Rating disagreements are more significant: (*i*) the lower is the quality of rated debt; (*ii*) the longer is debt maturity; (*iii*) the larger is the issue size which is associated with firm size; and (*iv*) the larger is the standard deviation in rating gap.[9] Coefficients on industry dummies show that except for insurance companies, which are closely related to banks, information uncertainty is relatively similar across the remaining industries. Further, observe that for banks, participation

[9]The coefficient estimates can be interpreted as how a small change in the continuous variables may result into the change in the probability of a split rating. For example, from column (1) of Table 5, increase in the rating increases the changes of disagreement by 6.4%.

Table 4: Bank Asset Composition and Capital

Summary statistics cover 3,464 new bonds issued by publicly traded banks or bank holding companies reported in the SDC database in the 80 quarters spanned by the period 1991 through 2010. Bank asset composition and capital are obtained from the Federal Reserve Y9-C Bank Holding Company Call Reports. Values are expressed in millions of dollars except for percentages. [a]Securities purchased are either held-to-maturity or available for sale. [b]Trading assets are debt and equity securities bought and sold principally in the near term [c]Risk-weighted capital ratios are computed as quarterly average equity divided by risk-weighted assets. Weights are defined by risk-sensitivity ratios under the 1989 Basel Accord. Definitions of asset composition and capital are detailed in Appendix C.

	Mean	**% of Total Assets**	**25th Percentile**	**Median**	**75th Percentile**	**Standard Deviation**
Cash	20,170	4.70%	2.09%	5.78%	12.14%	4.74%
Federal Funds and Repurchases	9,644	2.25%	0.13%	1.50%	4.78%	3.32%
Securities[a]	53,161	12.39%	4.90%	11.23%	29.47%	12.62%
Trading Assets[b]	65,116	15.18%	0.74%	7.23%	27.58%	21.89%
Total Loans	207,110	48.27%	21.34%	58.89%	146.78%	40.47%
Residential Real Estate Loans	65,879	15.35%	4.93%	16.39%	45.83%	15.67%
Commercial Real Estate Loans	17,552	4.09%	2.08%	5.75%	9.32%	3.45%
Other Loans	123,678	28.83%	14.21%	35.40%	69.64%	24.19%
Premises	3,770	0.88%	0.49%	1.42%	2.77%	0.57%
Intangible Assets	12,186	2.84%	0.21%	0.98%	5.40%	3.99%
Other Assets	57,906	13.50%	1.88%	4.49%	15.56%	21.15%
Total Assets	429,062	100.00%	100.00%	100.00%	100.00%	100.00%
Risk-weighted Capital[c]	9.19%	9.19%	7.84%	8.82%	10.56%	2.12%

Table 5: Rating Agency Disagreements, Bond Characteristics, and Issuer Type

Columns (1)-(4) report coefficient estimates from logit regressions of the probability of split rating changes, and columns (5)-(8), ordered probit regressions of the absolute ratings gap. All regressions include unreported year dummies for all years except the crisis year 2008. Standard errors are shown in parentheses. [a]SPLIT = 0 if Moody's = S&P, and 1 if Moody's ≠ S&P. [b]Absolute gap =|Moody's – S&P| [c]Average of Moody's and S&P ratings; higher values indicate higher risk. [d]Bank*MBS refers to banks that issued mortgage-backed securities during the sample period. *. **. *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. SIC codes used to classify industries are detailed in Appendix B.

	SPLIT[a]				|Moody's – S&P|[b]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Issue Characteristics								
Average Rating[c]	0.064*** (0.002)	0.064*** (0.002)	0.051*** (0.003)	0.053*** (0.003)	0.056*** (0.002)	0.057*** (0.002)	0.046*** (0.002)	0.047*** (0.003)
Maturity (years)	0.012*** (0.001)	0.012*** (0.001)	0.006*** (0.001)	0.007*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
Face Value ($10M)	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Standard Deviation of Rating Gap				0.107*** (0.014)				0.124*** (0.012)
Issuer Type								
Bank	0.828*** (0.023)	0.708*** (0.032)			0.793*** (0.020)	0.591*** (0.028)		
Bank × MBS Issue[d]		0.229*** (0.042)				0.377*** (0.036)		
Other								
Manufacturing			-0.680*** (0.031)	-0.681*** (0.031)			-0.684*** (0.027)	-0.686*** (0.028)
Mining			-0.790*** (0.053)	-0.770*** (0.056)			-0.766*** (0.048)	-0.747*** (0.050)
Trade			-0.563*** (0.045)	-0.566*** (0.047)			-0.598*** (0.040)	-0.611*** (0.042)
Services			-0.688*** (0.043)	-0.677*** (0.044)			-0.718*** (0.038)	-0.716*** (0.040)
Transportation			-0.693*** (0.062)	-0.804*** (0.064)			-0.607*** (0.055)	-0.720*** (0.057)
Public Utilities			-0.630*** (0.034)	-0.663*** (0.035)			-0.621*** (0.030)	-0.651*** (0.031)
Insurance			-0.500*** (0.053)	-0.547*** (0.055)			-0.421*** (0.047)	-0.464*** (0.049)
Other Finance and Real Estate			-0.954*** (0.025)	-0.924*** (0.026)			-0.907*** (0.022)	-0.874*** (0.023)
All Other			-1.047*** (0.083)	-1.101*** (0.085)			-0.987*** (0.077)	-1.027*** (0.079)
Pseudo R^2	0.117	0.119	0.129	0.136	0.101	0.106	0.110	0.118
Number of Observations	25,652	25,652	25,652	24,739	25,652	25,652	25,652	24,739

in mortgage-backed asset securitization activities increased asset complexity and opacity. Coefficients for bank and bank interacted with mortgage-backed securitization are positive and statistically significant.

C.2 Information Uncertainty of Banks

But why are banks opaque? Morgan (2002) argues that banks are inherently opaque because of the unique nature of bank assets and its use of leverage. Logit and ordered probit regressions reported in Table 6 examine the impact of asset composition and capital, as well as participation in mortgage-backed asset securitization activities, on the likelihood of a rating split and the magnitude of the absolute rating gap. *Other assets*[10], which are used as the benchmark, are excluded in the regressions.

The Chi-square test that the asset composition coefficients are jointly zero confirms that bank assets influence the likelihood and magnitude of rating disagreements. As expected, the coefficients on securities and trading assets, as well as total loans are significantly positive, and significantly negative, on premises and intangible assets. The significant positive coefficient sign on cash and federal funds, which are presumably more transparent, is consistent with the agency costs of high free cash flow (Jensen and Meckling, 1976). Further, ratings disagreements are more significant: (*i*) the lower is the quality of rated debt; (*ii*) the longer is the debt maturity; and (*iii*) the larger is the issue size which is associated with firm size.

Contrary to Morgan (2002), however, the coefficient on capital is significantly positive. The explanation is twofold. The first is the difference in sample period. Banks were not actively involved in asset securitization and complex derivatives during Morgan's (2002) sample period 1983-1993. Second, as Iannotta (2006) notes, bank capital may proxy for omitted sources of

[10] Other assets are total assets minus loan, securities, trading assets, cash, federal funds, premises and intangibles, scaled by total assets.

Tables 6A and 6B: Bank Holding Company Assets and Rating Agency Disagreements

Table reports ordered probit and multinomial logit with fixed effects regressions of the absolute difference between Moody's and S&P ratings of new bond issues against bank asset composition and capital. Bank asset composition and capital variables are expressed as percentages of total assets. Risk-Weighted Capital ratios computed as quarterly average equity divided by risk-weighted asset. Weights are defined by risk-sensitivity ratios under the Basel Accord. Total assets are in billions of dollars. *. **. *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6A	Absolute Ratings Gap: |Moody's – S&P| Ordered Probit							
	Coefficient Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq	Coefficient Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq
Assets								
Cash and Federal	2.733***	0.784	12.159	0.001	2.639***	0.796	10.977	0.001
Securities & Trading Assets	1.352*	0.773	3.057	0.080	1.448*	0.804	3.240	0.072
Total Loans	2.799***	0.648	18.632	<.0001	2.56***	0.667	14.737	0.000
Premises and	-2.272	2.474	0.844	0.358	-0.799	2.605	0.094	0.759
Risk-Weighted	-2.872	1.931	2.213	0.137	4.743**	2.321	4.178	0.041
Total Assets	1.628***	0.169	92.689	<.0001	1.783***	0.190	88.569	<.0001
Square Total	-0.419***	0.076	30.355	<.0001	-0.416***	0.081	26.131	<.0001
MBS					1.219***	0.209	34.166	<.0001
MBS*Risk-Weighted Capital					-14.009***	2.377	34.749	<.0001
Bond Characteristics								
Average Rating	-0.035*	0.018	3.738	0.053	-0.025	0.018	1.894	0.169
Maturity, years	0.008**	0.003	5.519	0.019	0.009**	0.003	6.184	0.013
Face Value ($10 mil)	-0.001***	0.000	7.612	0.006	-0.001**	0.000	6.378	0.012
Year Dummies (excluding 2008)								
1991	1.722***	0.246	48.865	<.0001	1.827***	0.249	54.029	<.0001
1992	1.335***	0.228	34.396	<.0001	1.475***	0.231	40.940	<.0001
1993	1.339***	0.216	38.537	<.0001	1.540***	0.220	49.090	<.0001
1994	0.639***	0.212	9.080	0.003	0.816***	0.216	14.300	0.000
1995	0.235	0.209	1.265	0.261	0.430***	0.213	4.088	0.043
1996	0.113	0.206	0.302	0.582	0.284	0.210	1.833	0.176
1997	0.272	0.202	1.816	0.178	0.377*	0.204	3.407	0.065
1998	1.101***	0.197	31.207	<.0001	1.196***	0.199	36.042	<.0001
1999	1.135***	0.198	32.860	<.0001	1.269***	0.201	39.945	<.0001
2000	1.490***	0.197	57.275	<.0001	1.612***	0.200	65.289	<.0001
2001	1.425***	0.199	51.526	<.0001	1.540***	0.201	58.620	<.0001
2002	1.793***	0.205	76.506	<.0001	1.880***	0.207	82.455	<.0001
2003	1.794***	0.204	77.439	<.0001	1.864***	0.206	82.025	<.0001
2004	1.787***	0.199	80.946	<.0001	1.884***	0.201	88.067	<.0001
2005	1.652***	0.198	69.928	<.0001	1.729***	0.200	75.092	<.0001
2006	1.368***	0.191	51.465	<.0001	1.433***	0.192	55.494	<.0001
2007	0.804***	0.183	19.299	<.0001	0.812***	0.184	19.528	<.0001
2009	0.574	0.265	4.702	0.030	0.571**	0.264	4.677	0.031
2010	0.730***	0.262	7.735	0.005	0.791***	0.264	9.007	0.003
Pseudo R^2	0.301				0.310			
Joint Significance	0.000				0.000			
Number of Obs. Observations	3,464				3,464			

Table 6B	**Absolute Ratings Gap: |Moody's – S&P|** **Logit**(with fixed effects)							
	Coefficient Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq	Coefficient Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq
Assets								
Cash and Federal	1.949***	0.510	3.820	0.000	1.894***	0.518	3.660	0.000
Securities & Trading	0.943*	0.504	1.870	0.061	0.978*	0.524	1.870	0.062
Total Loans	1.978***	0.422	4.690	<.0001	1.775***	0.434	4.090	<.0001
Premises and	-2.073	1.626	-1.270	0.203	-0.850	1.691	-0.500	0.615
Risk-Weighted Capital	-1.469	1.249	-1.180	0.240	4.304***	1.500	2.870	0.004
Total Assets	1.209***	0.112	10.840	<.0001	1.312***	0.122	10.750	<.0001
Square Total Assets	-0.327***	0.051	-6.450	<.0001	-0.320***	0.053	-5.990	<.0001
MBS					0.939***	0.135	6.950	<.0001
MBS×Risk-Weighted Capital					-10.736***	1.532	-7.010	<.0001
Bond Characteristics								
Average Rating	-0.022*	0.012	-1.840	0.066	-0.014	0.012	-1.150	0.251
Maturity (years)	0.004*	0.002	1.640	0.101	0.004*	0.002	1.800	0.073
Face Value ($10M)	-0.001***	0.000	-3.080	0.002	-0.001**	0.000	-2.760	0.006
Year Dummies (excluding 2008)								
1991	1.238***	0.159	7.800	<.0001	1.304***	0.158	8.250	<.0001
1992	0.851***	0.145	5.870	<.0001	0.947***	0.145	6.540	<.0001
1993	0.935***	0.137	6.850	<.0001	1.077***	0.137	7.850	<.0001
1994	0.408***	0.133	3.070	0.002	0.535***	0.133	4.020	<.0001
1995	0.194	0.129	1.500	0.133	0.340***	0.130	2.610	0.009
1996	0.128	0.127	1.010	0.312	0.256**	0.127	2.020	0.044
1997	0.198	0.124	1.590	0.111	0.272**	0.124	2.190	0.029
1998	0.690***	0.123	5.620	<.0001	0.757***	0.122	6.180	<.0001
1999	0.693***	0.124	5.610	<.0001	0.789***	0.123	6.390	<.0001
2000	0.963***	0.123	7.840	<.0001	1.047***	0.123	8.550	<.0001
2001	0.902***	0.124	7.270	<.0001	0.983***	0.124	7.940	<.0001
2002	1.183***	0.129	9.190	<.0001	1.243***	0.128	9.700	<.0001
2003	1.171***	0.128	9.160	<.0001	1.218***	0.127	9.570	<.0001
2004	1.148***	0.125	9.220	<.0001	1.216***	0.124	9.800	<.0001
2005	1.052***	0.124	8.470	<.0001	1.106***	0.124	8.940	<.0001
2006	0.856***	0.120	7.140	<.0001	0.902***	0.119	7.550	<.0001
2007	0.483***	0.115	4.200	<.0001	0.488***	0.114	4.280	<.0001
2009	0.341**	0.168	2.030	0.042	0.327**	0.167	1.960	0.051
2010	0.433***	0.169	2.570	0.010	0.500***	0.168	2.980	0.003
Pseudo R^2	0.263				0.273			
Joint Significance ssets	0.000				0.000			
Number of Observations	3,464				3,464			

opacity. That is, a higher level of risk-weighted capital compensates for lower asset quality not captured in asset composition.

This conjecture is confirmed in the second column of Table 6A where risk-weighted capital is interacted with a mortgage-backed asset securitization dummy variable. Results show that rating splits banks are more likely for banks involved with mortgage-backed asset securitization, but high risk-weighted capital mitigates the likelihood of a rating split. In other words, rating disagreements increase with the asset complexity but information uncertainty concomitant with complexity can be offset by maintaining higher risk-weighted capital.

Lastly, coefficients on year dummies show that deregulation events, which are associated with the demise of "too big to fail" after 1986, the Interstate Banking and Branching Efficiency Act of 1994, and the Gramm-Leach-Bliley Act of 1998, increased the likelihood and magnitude of split ratings. The increase in competition from deregulation reduces bank profitability, and the resulting adverse impact on market equity, diminishes the regulatory threat of an operating charter loss on the risk exposure and capital adequacy of banks (Keely, 1990).Assuming that only the highest quality debt could be issued in the 2008 crisis year, the large decline in year dummy coefficients pre-2008, and small rise post-2008, suggests that the quality of bank debt issues improved in the years leading up to the financial crisis and remained relatively high after the financial crisis.

Table 7, which divides banks into two subgroups by the median risk-weighted capital ratio, examines the impact of mortgage-backed asset securitization activities on rating disagreement controlling for issue characteristics, firm size, and year dummies. Two observations can be made. First, for poorly capitalized banks, loans and trading

Table 7: Impact of Bank Capital on Information Uncertainty

Table reports ordered probit regressions of the absolute difference between Moody's and S&P ratings of new bond issues for banks below and above the median capital ratio across banks each year. Bank asset composition and capital are expressed as percentages of total assets. Total assets are in billions of dollars. *. **. *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Risk-Weighted Capital < Median				Risk-Weighted Capital >Median			
	Coefficient Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq	Coefficient Estimate	Standard Error	Wald Chi-Square	Pr>ChiSq
Assets								
Cash and Federal Funds	7.778***	1.323	34.568	<.0001	1.244	1.347	0.852	0.356
Securities & Trading Assets	6.304***	1.404	20.168	<.0001	1.388	1.258	1.218	0.270
Total Loans	8.353***	1.190	49.235	<.0001	0.637	1.034	0.380	0.538
Premises and Intangibles	-14.277***	5.308	7.233	0.007	0.859	3.757	0.052	0.819
Risk-Weighted Capital	14.71***	4.801	9.387	0.002	2.408	3.176	0.575	0.448
Total Assets	2.749***	0.375	53.754	<.0001	1.904***	0.272	48.878	<.0001
Square Total Assets	-0.668***	0.138	23.403	<.0001	-0.730***	0.144	25.664	<.0001
MBS	1.198***	0.370	10.491	0.001	1.069***	0.306	12.173	0.001
MBS*Risk-Weighted Capital	-15.362***	4.769	10.378	0.001	-13.024***	3.297	15.603	<.0001
Bond Characteristics								
Average Rating	-0.122***	0.031	15.766	<.0001	0.030	0.024	1.522	0.217
Maturity (years)	0.013***	0.005	7.053	0.008	0.007	0.005	1.922	0.166
Face Value ($10M)	-0.001**	0.001	4.091	0.043	0.000	0.001	0.337	0.561
Year Dummies (excluding 2008)								
1991	3.429***	0.407	71.028	<.0001	0.538*	0.336	2.562	0.110
1992	2.428***	0.375	41.887	<.0001	0.671**	0.307	4.781	0.029
1993	2.567***	0.362	50.430	<.0001	0.334	0.294	1.288	0.256
1994	0.979***	0.354	7.665	0.006	0.433	0.285	2.310	0.129
1995	0.496	0.356	1.946	0.163	0.087	0.277	0.097	0.755
1996	-0.066	0.342	0.037	0.848	0.158	0.275	0.330	0.566
1997	0.469	0.340	1.906	0.167	-0.258	0.267	0.933	0.334
1998	1.151***	0.330	12.144	0.001	0.833***	0.259	10.306	0.001
1999	1.453***	0.322	20.379	<.0001	0.778***	0.266	8.532	0.004
2000	1.631***	0.324	25.374	<.0001	1.216***	0.262	21.463	<.0001
2001	1.368***	0.324	17.865	<.0001	1.335***	0.264	25.504	<.0001
2002	2.038***	0.335	37.092	<.0001	1.673***	0.270	38.408	<.0001
2003	2.062***	0.332	38.618	<.0001	1.628***	0.271	36.194	<.0001
2004	2.062***	0.317	42.242	<.0001	1.618***	0.264	37.677	<.0001
2005	2.110***	0.311	46.184	<.0001	1.123***	0.265	17.946	<.0001
2006	1.929***	0.294	43.126	<.0001	0.877***	0.257	11.655	0.001
2007	1.130***	0.269	17.702	<.0001	0.485**	0.253	3.670	0.055
2009	0.976**	0.412	5.610	0.018	0.135	0.368	0.134	0.714
2010	1.059***	0.408	6.736	0.009	0.575	0.362	2.527	0.112
Pseudo R^2	0.417				0.303			
Joint Significance	0.000				0.000			
Number of Obs	1,698				1,766			

securities increase the likelihood of rating split, but not for well-capitalized banks. Moreover, for poorly capitalized banks, premise and intangible asset significantly reduce ratings disagreement, but is not significant for well-capitalized banks. Second, for poorly and well capitalized bank groups, the coefficients on the mortgage-backed asset securitization dummy variable and its interaction with risk-weighted capital are significantly positive and negative respectively. Again, rating disagreements increase with the asset complexity but information uncertainty concomitant with complexity can be offset by higher risk-weighted capital holdings. The magnitude of coefficients also suggests that the importance of asset complexity and risk-weighted capital are greater for poorly capitalized banks.

C.3 Information Uncertainty and Market Microstructure

Table 8 reports logit and ordered probit regressions of the likelihood of a split rating and absolute ratings gap on variables that are market proxies for information uncertainty. In contrast to Flannery, Kwan, and Nimalendran (2004), the results show that ratings disagreements reflect market proxies of information uncertainty.

Ratings disagreements are more significant: (*i*) the higher is the bid-ask spread; (*ii*) the lower is trading volume which is associated with poor liquidity and less informed trading; and (*iii*) when the standard deviation and absolute error of analyst earnings (EPS) forecasts are high. The use of the number of analysts as a stand-alone proxy for information uncertainty exposes a potential endogeneity problem. Higher analyst coverage mitigates information asymmetry (Brennan and Subrahmanyam, 1995; Livingston, Naranjo, and Zhou, 2007) but opacity also creates a higher investor demand for information and analyst coverage. Controlling for the bid-ask spread, higher analyst coverage reduces the adverse selection costs to market makers of trading against informed investors.

Table 8: Rating Agency Disagreements and Market Proxies of Information Uncertainty

Columns (1)-(4) report coefficient estimates from logit regressions of split rating changes, and columns (5)-(8), ordered probit regressions of the absolute ratings gap, against proxies of security analyst and investor uncertainty. All regressions include unreported year dummies for all years except the crisis year 2008. Standard errors are reported in parentheses. [a]SPLIT = 0 if Moody's = S&P, and 1 if Moody's ≠ S&P. [b]Absolute gap =|Moody's – S&P|. [c]Average of Moody's and S&P ratings; higher values indicate higher risk. *. **. *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	SPLIT[a]				|Moody's – S&P|[b]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Proxies								
Number of Analysts	0.005*** (0.001)	-0.002** (0.001)	0.003*** (0.001)	0.001*** (0.001)	0.006*** (0.001)	-0.005*** (0.001)	0.004*** (0.001)	-0.003*** (0.002)
Standard Deviation of Annual EPS Forecasts	0.047*** (0.017)	0.025*** (0.017)	0.090*** (0.017)	0.074*** (0.017)	0.123*** (0.015)	0.101*** (0.015)	0.150*** (0.015)	0.133*** (0.015)
Absolute Error of Quarterly EPS Forecasts	0.029*** (0.004)	0.018* (0.003)	0.037*** (0.005)	0.024*** (0.004)	0.035*** (0.004)	0.026* (0.004)	0.043*** (0.005)	0.035*** (0.004)
Bid-Ask Spread/Price		1.001*** (0.465)		2.746*** (0.467)		2.472*** (0.419)		3.746*** (0.421)
Trading Volume		-2.954*** (0.000)		-2.971*** (0.804)		-1.333*** (0.635)		-1.601*** (0.647)
Issue Characteristics								
Average Rating[c]	0.013*** (0.002)	0.017*** (0.002)	0.002*** (0.002)	0.007*** (0.002)	0.008*** (0.001)	0.013*** (0.002)	-0.001*** (0.002)	0.007*** (0.002)
Maturity (years)	0.009*** (0.001)	0.004*** (0.001)	0.008*** (0.001)	0.003*** (0.001)	0.009*** (0.000)	0.004*** (0.001)	0.008*** (0.000)	0.003*** (0.000)
Face Value ($10M)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)
Standard Deviation of Rating Gap	0.058*** (0.006)	0.047*** (0.007)	0.047*** (0.006)	0.013 (0.007)	0.100*** (0.005)	0.058*** (0.006)	0.082*** (0.006)	0.023 (0.007)
Issuer Type								
Bank	0.728*** (0.015)	0.413*** (0.014)			0.592*** (0.013)	0.386*** (0.013)		
Bank × MBS Issue	0.113*** (0.018)	0.654*** (0.023)			0.321*** (0.015)	0.456*** (0.020)		
Manufacturing			-0.793*** (0.013)	-0.466*** (0.016)			-0.792*** (0.011)	-0.426*** (0.014)
Mining			-0.684*** (0.024)	-0.463*** (0.027)			-0.669*** (0.022)	-0.445*** (0.025)
Trade			-0.671*** (0.019)	-0.411*** (0.022)			-0.663*** (0.017)	-0.337*** (0.020)
Services			-0.604*** (0.019)	-0.329*** (0.022)			-0.671*** (0.017)	-0.354*** (0.020)
Transportation			-0.904*** (0.024)	-0.502*** (0.028)			-0.799*** (0.022)	-0.387*** (0.025)
Insurance			-0.530*** (0.017)	-0.131*** (0.021)			-0.591*** (0.015)	-0.184*** (0.018)
Public Utilities			-0.884*** (0.022)	-0.631*** (0.028)			-0.769*** (0.020)	-0.485*** (0.026)
Other Finance and Real Estate			-0.932** (0.015)	-0.423 (0.018)			-0.925*** (0.013)	-0.410*** (0.016)
All Other			-1.109*** (0.036)	-0.778*** (0.038)			-1.061*** (0.034)	-1.708*** (0.036)
Pseudo R^2	0.569	0.308	0.602	0.291	0.695	0.297	0.699	0.286
Number of Observations	10,111	7,983	10,111	7,983	10,111	7,983	10,111	7,983

C.4 Market Prices and Information Uncertainty

Table 9 examines the impact of rating split and industry on the equity market reaction to new debt issues, controlling for the volatility of equity returns, as well as, firm and issue characteristics. The dependent variable in these regressions are the annualized abnormal holding period equity returns over the 62-day event window (-60, +1) around the issue date. Columns (1)-(3) compare banks to nonbanks, and columns (4)-(6), nonbank firms in other industries against banks.

Overall, the results that informational asymmetries between insiders and outsiders make external financing costly. In all regressions, intercepts verify that average equity market reactions to new debt issues, regardless of industry, are always significantly negative, and are more negative, the higher is the volatility of equity returns. Moreover, that the coefficients on split rating are insignificant in regressions (2)-(3) which compare banks against nonbanks, but significant in regressions (5)-(6) which compare nonbanks against banks, confirm the results in Table 8 that rating disagreements imbed market proxies of information uncertainty. Further, observe that the coefficient on banks in regression (1) and coefficients on the interaction of split rating and banks in regressions (2)-(3) are statistically significant. Moreover, the coefficients on non-bank industries in regression (4) and coefficients on the interaction of split rating and non-bank industries in regressions (5)-(6) are insignificant. These results indicate that equity returns surrounding new debt issues by banks are notably lower. Information uncertainty about banks is more significant.

Table 9: Holding Period Returns and Rating Agency Disagreements

Columns (1)-(6) report regressions of holding period returns against rating agency disagreements clustered by firm and with year dummies. Bank asset composition and capital are expressed as percentages of total assets. Total assets are in billions of dollars. [a]Holding Period Returns are annualized cumulative abnormal returns around a 62-day window (-60,+1) computed as the difference between daily and CRSP equal-weighted index returns, and annualized standard deviation, computed from daily returns (-60,+1). [b]In regressions (3) and (6), split is computed as the inverse logistic transform of the residuals in a first-stage logistic regression of split against all other independent variables in the second-stage holding period returns regressions.

	Holding Period Returns[a]					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-3.290*** (1.109)	-2.580*** (0.905)	-1.108** (0.597)	-0.528* (0.388)	-0.475*** (0.201)	-0.094 (0.247)
Standard Deviation	-1.832 (1.889)	-0.821 (0.896)	-1.801 (1.282)	1.173 (0.513)	-0.301* (0.194)	1.441 (0.525)
Issue Characteristics						
Average Rating	0.094 (0.053)	0.094 (0.053)	0.158 (0.047)	0.058 (0.024)	0.054 (0.011)	0.058 (0.012)
Maturity (years)	0.000 (0.014)	0.000 (0.014)	-0.014 (0.010)	0.002 (0.004)	0.000 (0.013)	0.001 (0.004)
Face Value ($10M)	-0.001 (0.004)	-0.001 (0.004)	-0.002 (0.004)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Firm Characteristics						
Total Assets	1.329 (1.486)	1.684 (1.370)	0.661 (0.613)	0.009 (0.027)	0.000** (0.000)	0.000 (0.000)
Capital Ratio	14.263** (5.733)	13.536** (5.345)	0.735 (4.649)	0.081 (0.210)	-0.063 (0.180)	0.005 (0.196)
Issuer Type						
Bank	-0.805* (0.351)					
Bank × MBS	-0.035 (0.288)					
Manufacturing				0.044 (0.097)		
Mining				-0.039 (0.163)		
Trade				-0.148 (0.130)		
Services				0.127 (0.129)		
Transportation				-0.001 (0.158)		
Insurance				-0.010 (0.155)		
Public Utilities				-0.093 (0.120)		
Other Finance and Real Estate				0.184 (0.103)		
All Other				0.282 (0.215)		
Market Proxies						
Number of Analysts	0.025* (0.019)	0.021 (0.018)	0.007 (0.018)	0.008* (0.006)	0.003 (0.05)	0.007 (0.018)
Standard Deviation of Annual EPS Forecasts	1.728 (1.081)		1.724 (1.144)	-0.122* (0.094)	-0.160** (0.076)	1.724 (1.144)

Absolute Error of Quarterly EPS Forecasts	-0.199*	-0.192*	-0.048*	-0.006*		-0.048*
	(0.114)	(0.122)	(0.166)	(0.017)		(0.166)
Bid-Ask Spread/Price	9.251		5.347	-21.518***	-43.377***	5.347
	(27.304)		(28.121)	(6.832)	(6.368)	(28.121)
Trading Volume	45.416		23.079	1.033		23.079
	(67.817)		(82.789)	(3.795)		(82.789)
Rating Disagreement						
Split[b]		-0.232	0.002		-0.137*	-0.615
		(0.194)	(0.017)		(0.103)	(0.259)
Split × Bank		-0.986***	-0.039*			
		(0.347)	(0.188)			
Split × Bank × MBS		0.249	0.341			
		(0.341)	(0.502)			
Split × Manufacturing					0.001	0.041
					(0.123)	(0.183)
Split × Mining					0.233	0.017
					(0.222)	(0.320)
Split ×Trade					0.005	-0.269
					(0.175)	(0.250)
Split ×Services					-0.235	0.081
					(0.172)	(0.245)
Split ×Transportation					-0.008	-0.044
					(0.225)	(0.315)
Split × Insurance					-0.040	-0.241
					(0.235)	(0.312)
Split × Public Utilities					-0.151	-0.200
					(0.150)	(0.226)
Split × Other Finance and Real Estate					-0.001	0.157
					(0.148)	(0.207)
Split × All Other					0.043	0.330
					(0.359)	(0.453)
Pseudo R^2	0.065	0.063	0.067	0.012	0.017	0.019
Number of Observations	7,983	7,983	7,983	7,983	7,983	7,983

D. Conclusion

In this study, we use disagreements on dual-rated debt issues by firms to proxy for information uncertainty. The 20-year sample period 1991-2010covers three major deregulatory events – the demise of "too big to fail" after 1986, the Interstate Banking and Branching Efficiency Act of 1994, and the Gramm-Leach-Bliley Act of 1998, as well as the years prior and subsequent to the financial crisis in 2008. We validate Morgan's (2002) finding that rating splits are more likely, and the magnitude of rating gaps are larger, for banks relative to nonbanks. Asset composition and capital are inherent sources of information uncertainty for banks. Opacity is more severe for banks with higher loan and trading asset holdings and lower risk-weighted capital.

Additionally, we extend Morgan's (2002) findings. First, participation by banks in mortgage-backed asset securitization increases its complexity and opacity. Second, the deregulation of the banking industry, which intensified competition and reduced the discipline of charter value, also contributed to increased information uncertainty. Third, the large decline in the significance of rating disagreements pre-crisis and small rise post-crisis suggests that the quality of bank debt issues improved in the years leading up to 2008 and remained relatively high subsequently.

Importantly, we also show that rating disagreements reflect market proxies of information uncertainty. In particular, information uncertainty is lower, when analyst coverage is higher, and the standard deviation and absolute error of analyst earnings forecasts are lower. Low trading volume and high bid-ask spreads are associated with more significant rating disagreements.

Last but not least, markets price information uncertainty. Opacity increases the informational asymmetry between insiders and outsiders and makes external financing more costly. Equity returns surrounding new debt issues are significantly negative on average, and notably lower, for banks compared to nonbanks. Information uncertainty impedes market discipline and substantiates the need for regulation and supervision of banks to prevent excessive risk taking, enforce capital adequacy standards, and constrain activities that intensify systemic risks.

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Appendix A: Numerical vs. Letter Ratings

Numerical Rating	S&P Rating	Moody's Rating
1	AAA	Aaa
2	AA+	Aa1
3	AA	Aa2
4	AA-	Aa3
5	A+	A1
6	A	A2
7	A-	A3
8	BBB+	Baa1
9	BBB	Baa2
10	BBB-	Baa3
11	BB+	Ba1
12	BB	Ba2
13	BB-	Ba3
14	B+	B1
15	B	B2
16	B-	B3
17	CCC+	Caa1
18	CCC	Caa2
19	CCC-	Caa3
20	CC	Ca
21	C	C

Appendix B: Industry Classification Standard

Industrial Sector	SIC Codes
Bank	6021, 6022, 6029, 6712 or 6719
Manufacturing	20-39
Mining	10-14
Transportation	41-47
Trade	50-59
Other Finance and Real Estate	60 other than 6021, 6022, 6029, 6712, 6719, 6311, 6321, 6324, 6331, 6351, 6361,6399, 6411
Services	70-89
Public Utilities	40,48-49
Insurance	6311, 6321, 6324, 6331, 6351, 6361,6399, 6411
All Other	01-09, 15-17, 52

Appendix C: Bank Capital and Asset Composition

Variables from the FR Y-9C call reports used to describe bank asset composition and capital in this study are defined below. Balance sheet items are the end of quarter values. Unless otherwise specified, all variables are scaled by total assets.

TA	Total inflation-adjusted assets	BHCK2170
CASH	Cash and Noninterest-bearing balances	BHCK0081+BHCK0395+BHCK0397
FF	Federal Funds and Repurchases	BHCK0276+BHCK0277, or BHCK1350, or BHDMB987+BHCKB989
RESREAL	Residential real estate loans and leases, net	BHDM1415+BHDM1420+BHDM1460+ BHDM1480
COMREAL	Commercial real estate loans and leases, net	BHDM1797+BHDM5367+BHDM5368
OTHLOAN	All other loans, net	BHCK2122~REALLOAN
TL	Total Loan	RESREAL+COMREAL+OTHLOAN
PREM	Premises	BHCK2145
IA	Intangible Assets	BHCK3163+BHCK0426
SEC	Held-to-maturity securities, available-for-sale securities	BHCK1754, BHCK1773 BHCK 0390 (prior to year 1993)
TRADE	Trading Assets	BHCK3545
OA	All others except cash, federal funds, total loan, securities, trading assets, premises, and intangible assets	1 – (CASH+FF+TL+SEC+TRADE +PREM+IA)/ASSETS
CAP	Equity capital	1– (BHCK2948/ASSETS)
RWC	Risk-weighted capital	BHCK3519/BHCK3368 (year1991-1995) BHCK3519/BHCKA223 (year1996-2000) BHCK7205 (year2001-2010)

Bank Corporate Governance, Opaque Assets and Risk

A. Introduction

Many analysts have blamed the dramatic collapse of the U.S. banking industry in 2007 and 2008, at least in part, on aggressive corporate governance.[11] Academic research generally supports the hypothesis that aggressive corporate governance incentives leads to greater risk-taking. Laeven and Levine (2009), for example, find that banks with more powerful owners tend to take greater risks. Adams, Hermalin and Weisbach (2010) find that banks receiving bailout funds had greater board independence than banks that did not receive bailout funds. Fortin, Goldberg and Roth (2010) find that BHCs with greater managerial control take less risk. Pathan (2009) finds that bank boards that reflect bank shareholders' interest increase bank risk-taking. In contrast, greater CEO power reduces bank risk-taking. A common methodology in this line of research is to regress various measures of bank risk directly on corporate governance variables.

Rather than focusing on a direct link between corporate governance and various risk measures, we argue that corporate governance incentives affect banks' asset choices, which ultimately determines the level of risk in the organization. The obvious motivation for investment in opaque assets is higher expected return. However, the greater investment in opacity also leads to higher systematic risk and lower idiosyncratic risk because opaque assets are difficult for investors to assess, which reduces their ability to analyze information particular to a single firm (Morck, Yeung, and Yu, 2000). The resulting price synchronicity makes firms more prone to crashes (Jin and Myers, 2006).

Our empirical methodology utilizes various measures of corporate governance to estimate their effect on banks' asset portfolios. We find that between the years 2000 and 2009, banks

[11] See Kirkpatrick (2009). Alan Blinder writes "I refer to the perverse incentives built into the compensation plans of many financial firms, incentives that encourage excessive risk-taking with OPM -- Other People's Money." *Wall Street Journal*, May 28, 2009.

with relatively aggressive corporate governance held more opaque assets than banks with relatively conservative corporate governance. We then estimate the effect of the marginal increase in opacity on the banks' systematic and systemic risk. We find strong evidence of higher systematic risk, but the evidence on systemic risk is mixed.

The paper proceeds as follows. Section 2 discusses the theoretical relationship between corporate governance and opacity, systematic and systemic risk. Section 3 introduces the data and variables. Section 4 provides the empirical results, and Section 5 concludes.

B. Corporate Governance, Opacity and Risk

Different corporate governance structures provide firms with different incentives for risk-taking. We focus on three of these incentive structures: incentive alignment between shareholders and managers, ownership structure, and board effectiveness. All else equal, banks that embed stronger shareholder incentives into managerial compensation will operate with more risk. Managers are typically risk-averse because, unlike shareholders, their human capital is invested with the firm and they are not well diversified; consequently, managers will choose a relatively low level of risk. But if compensation is heavily weighted towards aggressive performance targets through bonuses or through stock and option compensation, managers will act more in shareholder interests. Leaven and Levine (2009) find that bank risk is significantly higher in banks that have owners with large cash flow rights (managers). Owner controlled banks exhibit higher risk-taking behavior than banks controlled by managers with small shareholdings. However, studies of the financial crisis find at best a weak link between compensation structures and bank risk. Fahlenbrach and Stulz (2010) find no evidence that option compensation had an adverse impact on bank performance during the crisis. They also show that bank CEOs did not reduce their shareholdings in anticipation of nor during the crisis, nor did they hedge their equity exposure. Similarly, Acrey, McCumber and Nguyen (2011) find weak correlation between executive compensation focused on short-term performance and bank risk during the financial crisis.

In addition to compensation, strong bank boards with independent directors should encourage risk-taking because outsiders are, on average, more diversified than inside owners. Agrawal and Mandelker (1987) find that risk-taking and the degree of managerial control in non-financial firms are inversely related. Adams (2009) finds that U.S banks that received TARP funds had more independent boards. In addition to being more diversified, independent board members may lack the industry-specific banking knowledge necessary to monitor the actions of the CEO. Guerrera and Thal-Larsen's (2008) study eight major US financial institutions and find that two-thirds of directors had no banking experience. Moreover, many of the directors with little or no financial background sat on highly technical board committees covering audit and risk. For example, before the crisis, Northern Rock had only two board members with banking experience, and at Bear Stearns, six out of thirteen directors had no banking background. At Lehman Brothers, only one board member had financial sector knowledge. In a similar vein, greater blockholder ownership and bank risk-taking should be positively correlated because blockholders are typically well diversified institutional investors.

Board effectiveness can also vary by factors such as board size, classified boards, cumulative voting, dual appointment of the CEO as board chairman, and the presence of poison pills, and golden parachutes. When a bank board is more effective, i.e., better representing the bank shareholders' interests, shareholders prefer more risk taking. (Jensen and Meckling, 1976) This is also consistent with Pathan (2009) that stronger bank boards, captured by smaller board size, and more independent directors are positively related to bank risk taking because bank shareholders have preferences for excessive risk to take advantage of moral hazard derived from incomplete debt contract and limited liability.

Banks are inherently opaque because they make loans to businesses based on private information. Morgan (2002) determines that the banking industry is opaque relative to other industries because the incidence of split ratings on bond issues is higher in the banking industry. Opaque assets are more profitable than transparent assets (Jones, Lee, Yeager, 2011A). Consequently, it is reasonable to assume that banks with corporate governance structures that encourage risk-taking would hold more opaque assets than more conservatively governed banks.

Bank investments in opaque assets create more systematic risk, and potentially, more systemic risk. In their seminal paper, Morck, Yeung, and Yu (2000) find that stock prices exhibit more synchronicity in poor countries than in rich economies because the dearth of information makes it difficult for investors to trade on firm-specific information. Jin and Myers (2006) find that the cross-country variation in synchronicity reflects differences in opacity across countries. Outside investors bear less idiosyncratic risk and more systematic risk as opacity increases. Moreover, stocks of more opaque banks produce larger negative returns, and in conjunction with increased price synchronicity, raises the likelihood of a systemic market crash. Vallascas and Keasey (2009) find similar results for the banking industry. Using earnings management as a measure of opacity, Hutton, Marcus and Tehranian (2009) find that opacity is associated with higher systematic risk as measured by higher R-squared values in market model regressions. In addition, they find that opaque firms are more prone to stock crashes.[12]Haggard and Howe (2007) use the model of Jin and Myers (2006) to examine the relative opacity of banks

[12]They define the crash dummy variable as equal to one if the firm experiences one or more firm-specific weekly returns falling 3.09 standard deviations below the mean weekly firm-specific returns for that fiscal year; otherwise, the crash dummy value is set equal to zero.

and find that banks have less firm-specific information in their equity returns than industrial matching firms, consistent with banks being more opaque than industrial firms.

C. Data and Variable Descriptions

Our methodology consists primarily of 2SLS regressions where in the first stage we regress measures of corporate governance on bank asset composition. We then regress measures of systematic and systemic risk on the predicted loan composition to estimate the marginal effect of corporate governance on bank risk.

Our sample consists of publicly traded U.S. bank holding companies (BHCs) between 2001 and 2009.[13] Quarterly financial data on the BHCs come from the Federal Reserve FR Y-9C reports. Because the reporting threshold for the FR Y-9C was raised from $150 million to $500 million in 2006, the sample includes only BHCs with more than $500 million in inflation-adjusted assets in 2009 dollars. Stock market data come from the Center for Research in Security Prices (CRSP). The sample includes 199 BHCs and 6692 bank-quarter observations.

Loans and trading assets are a bank's primary sources of opacity. We decompose loans into commercial real estate loans (*COML*), residential real estate loans (*RESL*), and all other loans (*OTHL*). Trading assets (*TRADE*) are concentrated primarily in large banks; they consist of securities and derivative instruments that a bank intends to buy or sell on an ongoing basis. Other opaque assets (*OTHO)* includes (1) mortgage-backed securities, including non-agency issues, and (2) asset-backed securities, which include credit card receivables, home equity lines, automobile loans, other consumer loans, and commercial and industrial loans that are not explicitly or implicitly guaranteed by a federal government-related entity. Transparent assets (*TRANSP*) include cash, federal funds sold, securities purchased under agreements to resell.

[13] We refer to these entities either as "banks" or "BHCs" throughout the paper.

Banks corporate governance data are hand-collected from DEF 14A proxy statements of the annual meetings recorded in SEC's EDGAR filing, and yearly data from RiskMetrics (formerly IRRC) and Corporate Library.[14] Governance variables are chosen in part by data availability. The merger of data from FR Y-9C, CRSP, and Corporate Governance data results in 133 BHCs over the period from 2001 to 2009.

We use ten variables to proxy for corporate governance. COMP is the percentage of stock-based compensation; INSID is the percentage of insider ownership; INST is percentage of block-holding ownership, which is defined as more than 5% of total floating shares; and B_Index, the board index, is sum of seven dummy variables. Each of these seven dummy variables equals one when it signals aggressive board governance, and zero otherwise. Namely, board size equals one if the number of directors on the board is less than sample median because it is easier for smaller boards to reach agreements. Board director independence equals one if the percentage of independent directors is more than the sample median. An independent director has no existing or former employment relationship with the bank or its immediate family members and does not have any significant business ties with the bank. Classified board equals one if the board is not staggered; cumulative voting equals one if there is cumulative voting; CEO duality equals one if the CEO is not also the board chairman; poison pill equals one if the bank board has no provision for poison pill; and golden parachute equals one if no severance agreements exist that provide cash and noncash compensation to senior executives upon an event such as termination, demotion, or resignation following a change in control. To control for the delay in the impact of corporate governance on bank performance and risk-taking, we apply one-year lags of these corporate governance variables – COMP, INSID, INST, and B_Index, in empirical tests.

[14]Specifically, hand-collected governance variables include classified board, board size, CEO power, golden parachute, block-holder ownership, and poison pill.

A composite of governance Index ("G") is the sum of one point for the existence of 24 provisions from five categories: delay, protection, voting, other, and State. A composite index of entrenchment is measured with the "E" index, based on six provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments.. Since G_index and B_index shrink the sample size to less than 50 unique BHCs, they are reported only in summary statistics.

The regressions include several control variables. Credit risk is measured by non-performing loans (NPL), which are loans more than 90 days past due or no longer accruing interest. They are scaled by total assets. We expect that higher NPL leads to lower profitability and a reduced ability to invest in opaque assets. The capital ratio (CAP) is defined as the ratio of total equity to total assets. Because bank with more capital have more cushion to absorb adverse shocks, we would expect banks' performance during the crisis to be positively related to the capital ratio. The ratio of liquid assets to total asset (LIQ) captures liquidity risk. Generally, when trading assets are more liquid, markets function better. However, Myers and Rajan (1998) argue that the unusually liquid nature of trading securities can produce unintended consequences because it does not force the management of the institution to make credible commitments to investment strategies that protect investors – a characteristic that Morgan (2002) calls "slippery". The expected sign of liquidity is undetermined. The log of total asset (LNTA) and square of the log of total asset (SQLNTA) control for size differences among banks that may affect their performance. Return on average assets (ROA) is net income divided by average assets. We expect higher ROA to be correlated with higher risk.

We also computed measures of systematic and systemic risk. The three Fama-French

(1992) variables are used as risk proxies to calculate expected return in the model:[15]

$$\hat{Y} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{it} \quad (1)$$

where*MKT* is the daily equal-weighted CRSP index minus the risk free rate, *SMB* is the Fama-French daily size factor, and *HML* is the Fama-French daily value factor. Following Morck, Yeung, and Yu (2000) and Jin and Myers (2006), we measure stock market synchronicity by R^2as follows:

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n} (Y_i - \bar{Y}) - \sum_{i=1}^{n} (Y_i - \hat{Y})}{\sum (\bar{Y} i - \bar{Y})} \quad (2)$$

Here, $R^2$is the percent of the variation in the daily returns of each bank's stock return explained by variations in the U.S. market return, SSR is the sum of squared bank return variations, SST is the sum of squared total market return variations, and Y_i is each bank's stock return. It should be noted that the stock price synchronicity measure is unsuitable as a dependent variable in OLS regressions because they are bounded within the intervals [0,1]. Therefore we adopt a standard econometric remedy and apply the logistic transformation of R^2 to create phi as in equation (3):

$$\Phi = \log\left(\frac{R_i^2}{1 - R_i^2}\right) \quad (3)$$

Measures of systemic risk from the "cross-default" perspective can broadly be separated into two categories, one based on a structural approach using contingent claims analysis of the financial institution's assets, and the other on a reduced form approach focusing on the tail

[15]Beta1 is the coefficient of market factor in CAPM that applies the three-factor Fama-French (1992). R^2 is the part of stock return explained by market return for each BHC by each quarter. Φ is log-transformed R^2.

behavior of financial institutions' asset returns. In the first category, the limited liability of banks and presence of a negative externality of one bank's failure on the health of other banks give rise to a systemic risk-shifting incentive where all banks undertake correlated investments, thereby increasing economy-wide aggregate risk.

Lehar (2005) proposes a risk management approach to estimate the probability of a simultaneous default of several banks by using stock-market information. The second category applies to the asset correlation. Acharya (2009) modeled systemic risk as the endogenously chosen correlation of returns held by banks. Huang, Zhou and Zhu (2009) measure systemic risk by the price of insurance against financial distress, based on ex ante measure of default probabilities of individual banks and forecast asset return correlations. Specifically, they use realized correlations estimate from high-frequency equity return, and their results suggest that the theoretical insurance premium that would be charged to protect against losses that equal or exceed 15% of total liabilities of 12 major US financial firms.

We construct two measures of systemic risk. The first is the ratio of the bank return's skewness over the market return's skewness (a relative crash risk measurement). Following Jin and Myers (2006), crash likelihood measurement is defined as the skewness of residual returns, i.e., third moment of each stock's residual returns divided by the cubed standard deviation. Hutton, Marcus, and Tehranian (2009) measure crash as an indicator variable equal to one if within its fiscal year a firm experiences one or more firm-specific weekly returns falling 3.09 or more standard deviations below the mean firm-specific weekly return for its fiscal year and equal to zero otherwise. In this paper, we construct the ratio of bank return skewness to market return skewness to capture the relative crash frequency.

$$Skewness = \frac{E[(R_i - \mu)^3]}{E[(R_i - \mu)^2]^{3/2}} \quad (4)$$

$$Skewness\_Ratio = \frac{bank\_return\_skewness}{market\_return\_skewness} \quad (5)$$

We also construct the M3T_CORR as the second systemic risk measurement. M3T_CORR is defined as the asset weighted correlation composite of each bank's third moment OLS residual (M3T) with all other banks in the sample. The third moment OLS residual is asymptotically distributed as a normal random variable with mean 0 and variance of 6 times cubed second moment, defined as M_2 divided by N. The Coelli (1995) M3T statistics is superior to Jin and Myers (2006) simplified statistics because the M3T statistics is asymptotically normalized. Specifically,

$$\text{M3T} = M_3 / \sqrt{6M_2^3/N} \quad (6)$$

Instead of focusing on the "contemporaneous-default probability" as the skewness ratio, the M3T correlation emphasizes the "cross-default probability", i.e., the contagion of bank failure. The correlation of M3T is measured as follows and each bank is calculated a M3T correlation composite weighted by other correlating banks' asset size.

$$\rho_{M3T} = \text{Correlation of M3T across banks} \quad (7)$$

Table 1 describes the bank financial variables, market variables, corporate governance variables and control variables. The statistics show that banks in the sample have substantial variation. The mean inflation-adjusted asset size of sample banks is \$35.5 billion while median asset size is \$2.5 billion. On average, loans represent two-thirds of total assets. The components in the loan portfolio, *COML*, *RESL*, and *OTHL* represent 22%, 18%, and 26% of total assets respectively. *OPATRA* and *TRADE* are27% and 0.6% of total assets. Because the majority of banks in the sample hold no trading assets, the level of opaque trading assets varies widely across banks from zero to 33%. Average transparent asset is 6.9% of sample banks, ranging from zero to 59%.

All financial variables have wide ranges. For instance, average ROA is 0.88% during 2001 and 2009 and it ranges from -38.97% to 21.43%. LIQ ranges from 0.36% to 6.2%, and the average NPL from 0.04% to 0.37%. . Corporate governance variables also exhibit large cross-sectional differences. Median management ownership is 7.8% and it ranges from zero to 94%. The percentages of sample banks with CEO duality and golden parachutes are 61% and 81%, respectively. Sample banks hold on average 14 board members, 72% of classified board, and mean outside independent directors is 85% which ranges from 43% to 100%. Median block-holders ownership is 25%, ranging from zero to 96%. Finally, the E index medium is 3 with a minimum of 0 (strong governance) and maximum of 6 (weak governance).

The median R^2 of the sample is 27.3% and it ranges from zero to 82%. The log transformed R^2, Φ, has mean of -1.436, from -8.9 to 1.48. The skewness ratio has the mean of -0.048 and ranges from -45.05 to 66.45. The average of M3T_CORR is 0.09 and ranges from -0.27 to 0.63. Figure 1 plots the distribution of Φ, return skewness, skewness ratio, and M3T_CORR, respectively. This sample shows a high degree of concentration of R^2 around zero to 0.04, and log-transformed R^2 (Φ) is negatively skewed with average mean of -1.42.

Figure 2 shows the propensity to crash using the skewness of residuals as the measure of crash likelihood as in Jin and Myers (2006). [16] A crash is defined as a negative outlier in a firm's residual return. Lower values for skewness mean more negative outliers in the distribution of

[16] Sample has a positive skewness when the right tail is longer; the mass of the distribution is concentrated on the left of the figure. It has relatively few high values. The distribution is said to be right-skewed.

Table 1: Summary Statistics of BHCs

This table shows summary statistics of 199 bank holding companies with inflation adjusted assets (TA) greater than $500 million. Financial variables data are from quarter-end FY Y-9C, expressed as a percent of total assets. LOAN is the ratio of total loan to total assets; COML is commercial real estate loans; RESL is residential real estate loans; OTHL are all other loans; and OTHO are other opaque assets. TRADE is trading assets. TA is total inflation-adjusted assets in thousands USD. TRANSP is the % of transparent assets including cash, federal funds sold, securities purchased under agreement to resell, guaranteed AFS and HTM securities. ROA is net income over total asset. LIQ is the ratio of all liquid assets to total assets. NPL is the non-performing loans to total assets. CAP is the ratio of average equity to average asset. Market return data is collected from CRSP. R^2, the part of stock return explained by market return in CAPM that applies the three-factor Fama-French (1992) for each BHC by each quarter is log transformed into Phi. Skew ratio is defined as the ratio of each bank holding company's return skewness to the market return skewness by quarter. M3T_CORR is asset weighted correlation composite of each bank's M3T with all other banks in the sample. Corporate governance data is hand-collected yearly data from Proxy Statement, Risk-metrics, and Corporate Library. COMP is the percentage of stock-based compensation. INSID is the percentage of insider ownership. INST is percentage of block-holding ownership which is defined as more than 5% of total floating shares. B_Index is the sum of seven dummy variables: board size, board director independence, classified board, cumulative voting, CEO ownership, poison pill, and golden parachute. Each of the seven dummy variables equals one in favor of strong board governance and zero otherwise. Governance Index ("G") GI is sum of one point for the existence of 24 provisions from five categories: Delay, Protection, Voting, Other, and State. Entrenchment Index, EI, is based on six provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments.

Variable	N	Mean	Median	Maximum	Minimum	StdDev
LOAN	6692	0.66	0.68	0.93	0.04	0.14
COML	6692	0.22	0.21	0.81	0.00	0.16
RESL	6692	0.18	0.18	0.58	0.00	0.10
OTHL	6692	0.26	0.22	0.85	0.00	0.16
OTHO	6661	0.27	0.25	0.99	0.00	0.12
TRADE	6661	0.01	0.00	0.33	0.00	0.03
TRANSP	6692	0.07	0.05	0.59	0.00	0.08
TA	6692	3.55×10^7	2.53×10^6	2.361×10^9	4.99×10^5	1.84×10^8
ROA	6692	0.88	1.09	21.43	-38.97	1.89
LIQ	6692	1.65	0.325	6.20	0.04	0.32
NPL	6692	0.01	0.01	0.37	0.00	0.01
CAP	6692	0.09	0.09	0.80	0.00	0.05
RSQ	6692	0.27	0.27	0.82	0.00	0.20
PHI	6692	-1.44	-1.00	1.49	-8.94	1.53
SKEW RATIO	6692	-0.05	-0.05	66.45	-45.05	4.69
M3T_CORR	6692	0.09	0.08	0.63	-0.27	0.16
COMP	2744	0.57	0.58	1	0	0.24
INSID	2744	0.12	0.08	0.94	0	0.13
INST	2744	0.14	0.09	1	0	0.30
B_INDEX	2744	2.82	3	5	1	1.21
GI	1936	9.33	9	15	2	2.95
EI	1704	3.10	3	6	0	1.45

residual returns. It is evident from the figure that there is a high likelihood of a crash after 2007.

The sample statistics of financial variables vary widely over time as shown in Table 2. As expected, ROA falls sharply from 2001 to 2009 from 1.2% to 0.2% and NPL doubles from 0.5% to 1%. Banks hold more loan and opaque trading assets over time. Systematic risk as measured by Φ rises over time and idiosyncratic risk declines. The skew ratio declines while M3T_CORR increases significantly. Average bank systematic risk and the percentage of opaque asset over time is presented in Figure 3. It is apparent from the figure that opaque asset investment and bank systematic have the same upward. In contrast, corporate governance proxies are time-invariant variables and do not change significantly over time.[17]

In Table 3 is a correlation matrix of the key variables. The correlations for all key variables used in the study exhibit some notable patterns. Larger banks with higher systematic risk tend to have a higher percentage of stock-based compensation, less managerial ownership, less block-holder ownership, and stronger board governance. The skewness ratio has the opposite relationship with the corporate governance variables as expected. The transparent asset ratio is significantly negatively related with opaque assets and trading assets. Stock-based compensation is positively related with trading assets and most of the opaque assets. Inside ownership and block-holder ownership are negatively correlated with stock-based compensation. In general, banks with more stock-based compensation, less insider ownership, less block-holder ownership, and more effective board structure generally choose more opaque investments.

[17] It is suggested in Pathan (2009) that the estimation method of the relationship between corporate governance and bank risk-taking should be generalized least square random effect (RE) instead of fixed effect (FE). Stable corporate governance variables cannot be estimated with FE regression as it would be absorbed or wiped out in “within transformation’ or ‘time-demeaning’ process of FE. We tested FE in robustness checks and the results are consistent.

Figure 1A: Distribution of Φ

This figure plots the distribution of log transformed R^2, Φ, over 6,692 quarterly observations. Here, R^2 is the percent of the variation in the daily returns of each bank's stock return explained by variations in the U.S. market return. Stock price synchronicity measure is unsuitable as dependent variables in regressions because they are bounded within the intervals [0,1]. Therefore we adopt a standard econometric remedy and apply logistic transformations in equation. Specifically, Φ is defined as follows.

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$$\Phi = \log\left(\frac{R_i^2}{1-R_i^2}\right)$$

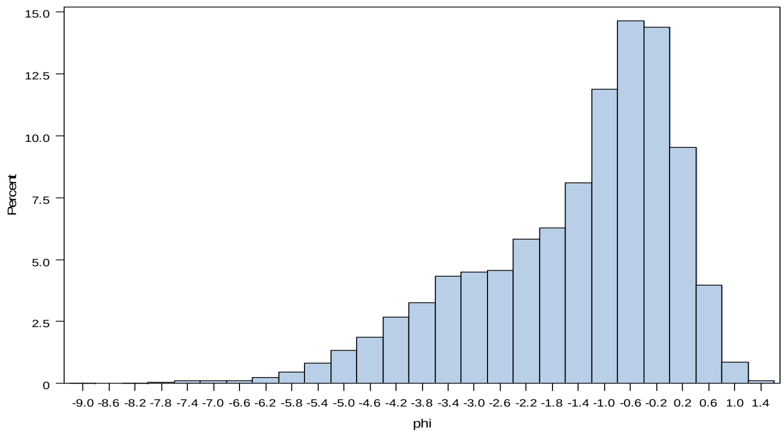

Figure 1B: Distribution of bank return skewness

This figure plots the distribution of bank return skewness, over 6,692 quarterly observations. Skewness is defined as the third moment of each stock's residual returns as follows.

$$skewness = \frac{E[(R_i - \mu)^3]}{E[(R_i - \mu)^2]^{3/2}}$$

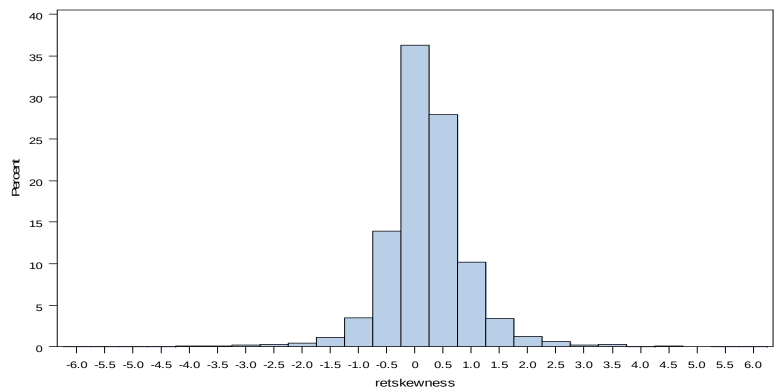

Figure 1C: Distribution of Skewness Ratio

This figure plots the distribution of bank return skewness ratio, over 6,692 quarterly observations. Skewness ratio is a relative crash risk measurement, defined as the ratio of bank return's skewness over market return's skewness.

$$\text{skewness\_ratio} = \frac{\text{bank\_return\_skewness}}{\text{market\_return\_skewness}}$$

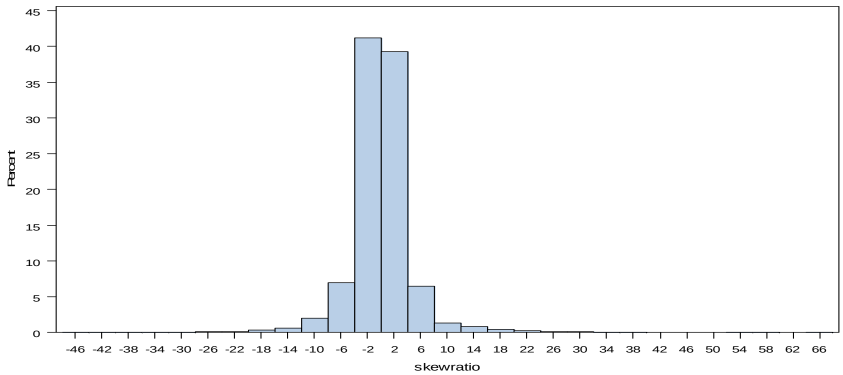

Figure 1D: Distribution of M3T_CORR

M3T_CORR is defined as the asset weighted correlation composite of each bank's third moment of OLS residual (M3T) with all other banks in the sample. The third moment of OLS residual is asymptotically distributed as a normal random variable with mean 0 and variance of "6 times cubed M2 divided by N". i.e., $M3T = \frac{M_3}{\sqrt{6M_2^3 / N}}$

Further, the M3T correlation emphasizes the "cross-default probability", i.e., the contagion of bank failure. The correlation of M3T is measured as follows and each bank is calculated a "M3T correlation composite" weighted by other correlating banks' asset size.

ρ_{M3T} = Correlation of M3T across banks

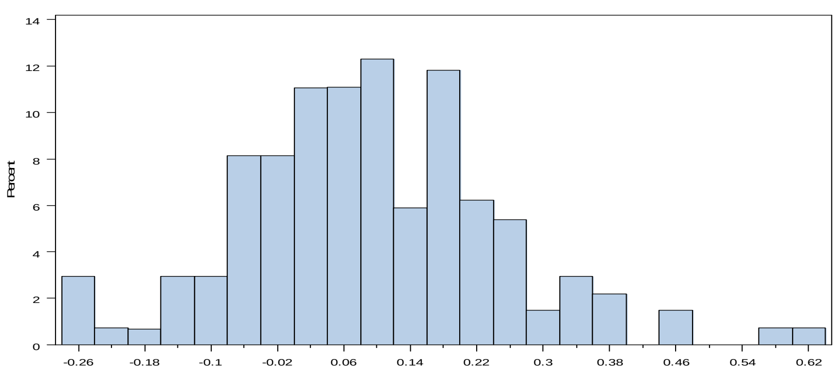

Figure 2: Propensity of Crash Increase over Years

Figure 2 graphs the propensity to crash using the skewness of residuals as the measure of crash likelihood as in Jin and Myers (2006). A crash is defined as a negative outlier in a firm's residual return. Lower values for skewness mean more negative outliers in the distribution of residual returns. It is evident from the figure that there is a high likelihood of a crash post 2007.

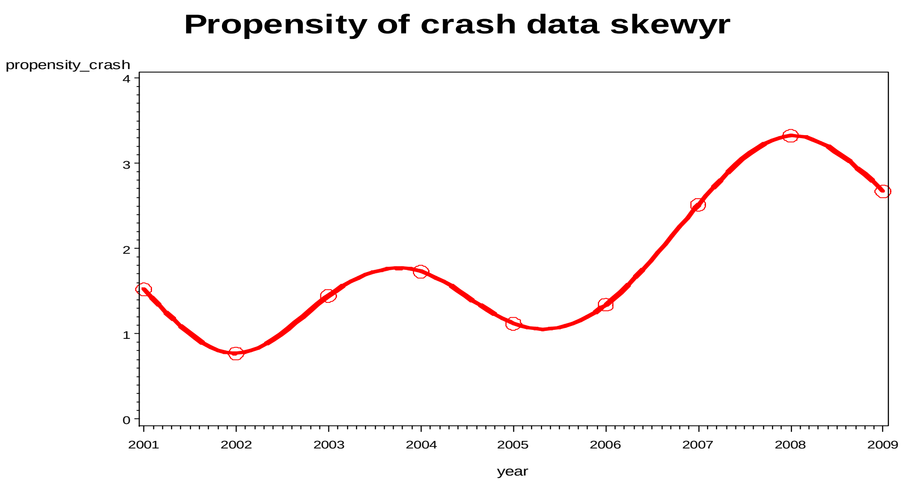

Figure 3: Bank Log-transformed R^2 and Opaque Investments Increase Over Years

Average bank systematic risk and the percentage of opaque asset over time is presented in Figure 3. Banks hold more loan and opaque trading assets over time. Also, systematic risk as measured by Φ rises over time.

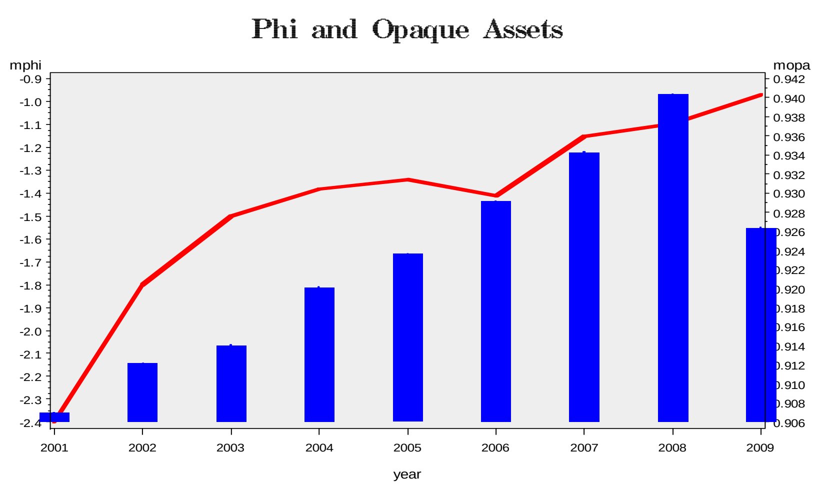

Table 2: Summary Statistics of BHCs by Period Subsamples

This table lists summary statistics of subsamples decomposed by period and quintile bank size. Samples are pre-crisis period from 2001 to 2006 and post crisis period from 2007 to 2009. Samples are further quintile-decomposed with decomposed by bank asset size. All variables are defined in Table 2.1

			Asset Composition							Control Variables			Ret	Risk				Corporate Governance					
		TA	LOAN	COML	RESL	OTHL	OTHO	TRADE	TRAN	LIQ	NPL	CAP	ROA	RSQ	Phi	Skew_R	M3T Corr	COMP	INSID	INST	BI	GI	EI
Pre-crisis (2001-2006)	mean	2.92×10^{7}	0.64	0.26	0.18	0.20	0.27	0.00	0.08	2.15	0.01	0.09	1.22	0.24	-1.61	0.02	0.05	0.58	0.12	0.14	2.73	9.61	2.92
	5th	6.37×10^{5}	0.39	0.04	0.02	0.04	0.11	0.00	0.00	0.15	0.00	0.06	0.43	0.01	-4.52	-6.00	-0.19	0.14	0.011	0.00	1.00	4.00	0.00
	25th	1.09×10^{6}	0.59	0.17	0.11	0.13	0.19	0.00	0.03	0.25	0.00	0.08	0.95	0.08	-2.51	-1.40	-0.03	0.43	0.04	0.05	2.00	8.00	2.00
	median	2.21×10^{6}	0.67	0.24	0.18	0.19	0.26	0.00	0.05	0.35	0.00	0.09	1.20	0.23	-1.20	-0.02	0.03	0.58	0.08	0.09	3.00	9.50	3.00
	75th	6.83×10^{6}	0.73	0.35	0.24	0.25	0.33	0.00	0.09	0.46	0.01	0.10	1.47	0.38	-0.49	1.24	0.15	0.79	0.14	0.15	4.00	12.00	4.00
	95th	8.46×10^{7}	0.82	0.53	0.35	0.39	0.47	0.02	0.24	0.85	0.01	0.12	1.97	0.56	0.23	6.04	0.32	0.93	0.37	0.39	5.00	14.00	5.00
	Std Dev.	1.44×10^{8}	0.14	0.14	0.10	0.10	0.13	0.03	0.09	39.14	0.00	0.04	0.91	0.18	1.49	4.89	0.15	0.24	0.13	0.37	1.22	2.88	1.43
	N	4526																1425					
During crisis (2007-2009)	mean	4.87×10^{7}	0.68	0.14	0.17	0.37	0.25	0.01	0.06	0.62	0.01	0.10	0.21	0.33	-1.08	-0.19	0.06	0.57	0.11	0.15	2.96	9.35	3.73
	5th	8.68×10^{5}	0.42	0.00	0.03	0.08	0.10	0.00	0.00	0.12	0.00	0.06	-2.81	0.02	-4.15	-6.77	-0.19	0.20	0.011	0.00	1.00	4.00	2.00
	25th	1.62×10^{6}	0.64	0.02	0.11	0.21	0.18	0.00	0.02	0.20	0.00	0.08	0.18	0.13	-1.94	-1.86	-0.04	0.44	0.04	0.06	2.00	8.00	3.00
	median	3.27×10^{6}	0.71	0.04	0.17	0.41	0.24	0.00	0.04	0.28	0.01	0.09	0.73	0.36	-0.57	-0.11	0.04	0.58	0.07	0.12	3.00	9.00	4.00
	75th	9.34×10^{6}	0.76	0.25	0.23	0.51	0.30	0.00	0.07	0.39	0.02	0.11	1.10	0.51	0.02	1.44	0.15	0.72	0.13	0.20	4.00	11.00	5.00
	95th	1.26×10^{8}	0.84	0.49	0.32	0.65	0.45	0.03	0.20	0.72	0.05	0.13	1.70	0.65	0.62	5.90	0.32	0.93	0.32	0.47	5.00	14.00	5.00
	Std Dev.	2.47×10^{8}	0.13	0.17	0.09	0.19	0.12	0.03	0.07	3.46	0.02	0.05	2.89	0.21	1.54	4.27	0.15	0.22	0.11	0.15	1.17	2.81	1.26
	N	2166																1319					
Diff. of Mean b/w sub-periods			0.04	-0.13	-0.01	0.17	-0.02	0.00	-0.02	-1.53	0.01	0.01	-1.01	0.09	0.52	-0.21	0.01	-0.01	-0.01	0.02	0.22	-0.26	0.81
Significance				***	**	***		***	***	***	***	***	***	***	*	***	*	***	***	***			***
Diff. of Median b/w sub-periods			0.04	-0.20	-0.01	0.21	-0.03	0.00	-0.01	-0.07	0.00	0.01	-0.47	0.13	0.63	-0.09	0.01	0.00	0.00	0.04	0.00	-0.50	1.00
Significance			***	***	***	**	***	***	***	***	***	***	***	***	***	**		**		***	***	**	***

D. Empirical Tests and Analysis

To motivate a bank's rationale for holding opaque assets, we first estimate the effect of opacity on bank profitability for the years 2001 through 2009. Table 4 presents results from regressing ROA on asset composition. Panel A lists results for the full sample, Panel B includes the boom years 2001-2006, and Panel C includes the financial crisis years 2007-2009. The overall results in Panel A show a positive relationship between opacity and profitability, though the results are somewhat mixed. The coefficient on the percentage of commercial real estate is positive but statistically insignificant, and the coefficient on other loans is negative and significant. The mixed results seem to be due to the differing effects of opacity on ROA in the boom years and the crisis years. Panel B, which reflects the boom years, shows a consistently positive relationship between opacity and ROA, thought the coefficients on other loans and other opaque assets are insignificant. Similarly, the coefficients on transparent assets are positive but insignificant. During the crisis years, opaque assets harm profitability. The coefficients on commercial real estate, residential real estate, and other loans are all negative, while the coefficient on transparent assets is positive and significant. The results overall indicate that opacity boosts profitability when the economic and real estate markets are strong.

Next we estimate the effects of various corporate governance incentives on bank asset composition. Table 5 shows the results from regressing commercial real estate loans, residential loans, other loans, other opaque assets, and transparent assets. We expect more aggressive corporate governance to lead to greater investment in opaque assets; consequently, we expect the coefficients on stock-based compensation, institutional ownership, and board index to be positive when regressed against commercial real estate, residential real estate, and other opaque assets.

Table 3: Correlation Matrix

This table shows the correlation matrix of sample variables. All variables are defined in Table 2.1. *, **, *** denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

	COML	RESL	OTHL	OTHO	TRADE	TRANSP	LIQ	NPL	CAP	ROA	RSQ	SKEW Ratio	COMP	INSID	INST	BI
COML	1															
RESL	-0.15	1														
OTHL	-0.63	-0.19	1													
OTHO	-0.23	-0.15	-0.27	1												
TRADE	-0.23	-0.08	-0.07	-0.03	1											
TRANSP	-0.19	-0.19	-0.14	-0.15	0.27	1										
LIQ	-0.24	-0.22	-0.24	0.58	0.14	0.4	1									
NPL	-0.26	-0.08	0.45	-0.2	-0.03	-0.02	-0.1	1								
CAP	0.08	-0.08	0.12	-0.08	-0.19	-0.12	-0.24	-0.08	1							
ROA	0.22	0.06	-0.35	0.14	0.00	0.01	0.04	-0.61	0.09	1						
RSQ	-0.14	0.04	0.05	0.04	0.1	0.02	0.03	-0.09	0.14	0.06	1					
SKEWRATIO	-0.06	0.02	0.06	-0.04	0.02	0.02	-0.01	-0.03	-0.03	-0.01	0.02	1				
COMP	-0.05	-0.07	-0.04	0.04	0.32	0.05	0.11	-0.06	-0.03	0.06	0.14	-0.03	1			
INSID	0.06	-0.17	0.02	0.01	-0.08	0.05	-0.04	0.07	-0.04	-0.04	-0.16	0	-0.06	1		
INST	0.04	-0.03	0	0	-0.08	-0.01	-0.01	0.04	0.05	-0.03	-0.06	0	0.01	0.28	1	
BI	-0.01	-0.04	-0.04	0.01	0.16	0.07	0.01	0.06	-0.02	-0.03	0.04	-0.03	-0.07	0.29	0.1	1

Table 4: Regressions of ROA on Bank Assets

Panel A lists results for the full sample, Panel B includes the boom years 2001-2006, and Panel C includes the financial crisis years 2007-2009. ROA is net income to average assets. Financial variables data are from quarter-end FY Y-9C, expressed as a percent of total assets. LOAN is the ratio of total loan to total assets; COML is commercial real estate loans; RESL is residential real estate loans; OTHL are all other loans; and OTHO are other opaque assets. TRADE is trading assets. TA is total inflation-adjusted assets in thousands USD. TRANSP is the % of transparent assets including cash, federal funds sold, securities purchased under agreement to resell, guaranteed AFS and HTM securities. ROA is net income over total asset. LIQ is the ratio of all liquid assets to total assets. NPL is the non-performing loans to total assets. CAP is the ratio of average equity to average asset. LN(TA) is natural log of total assets. SQLN(TA) is square of LN(TA). *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	**ROA**					
OLS	**Panel A 2001-2009**		**Panel B 2001-2006**		**Panel C 2007-2009**	
Intercept	-0.416		-3.532	***	4.314	
COML	0.102		0.321	***	-0.903	**
RESL	0.514	***	0.497	***	-0.284	
OTHL	-0.384	**	0.037		-0.935	***
OTHO	0.343	**	0.049		0.912	**
TRANSP	0.426	**	0.095		1.642	***
LIQ	-0.001	*	-0.001	***	-0.007	
CAP	14.687	***	14.095	***	15.332	***
NPL	-59.950	***	-36.385	***	-60.595	***
LN(TA)	-0.034		0.320	***	-0.536	
SQLN(TA)	0.002		-0.008	***	0.015	
Year Dummy: Yes						
District Dummy: Yes						
N	6692		4526		2166	
Adj R-Sq:	0.405		0.546		0.343	

Table 5: Regressions of Bank Assets on Corporate Governance Variables

This table shows the results from regressing commercial real estate loans, residential loans, other loans, other opaque assets, and transparent assets, respectively, on lagged corporate governance variables. Full sample results are in Panel A and the subsamples are in Panels B and C. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

	Panel A 2001-2009									
Dependent Variable	**COML**		**RESL**		**OTHL**		**OTHO**		**TRANSP**	
Intercept	0.538	***	-0.244	*	-0.532	***	0.286	**	0.956	***
L_COMP	0.002		0.033	***	0.017	*	0.017	**	-0.004	
L_INSID	0.015		0.038	***	0.018		-0.006		0.011	
L_INST	0.029	***	0.008	*	-0.036	***	0.000		0.000	
L_BI	-0.003	**	0.005	***	-0.010	***	0.009	***	0.000	
LIQ	-0.035	***	-0.053	***	-0.077	***	0.111	***	0.054	***
CAP	0.097		-0.747	***	0.512	***	-0.006		0.165	***
NPL	-0.207		-1.032	***	2.012	***	-0.870	***	0.094	
LN(TA)	-0.033		0.062	***	0.105	***	-0.022		-0.112	***
SQLN(TA)	0.000		-0.002	***	-0.003	***	0.001	**	0.003	***
Year Dummies: Yes										
Dist. Dummies: Yes										
R-Square	0.655		0.334		0.653		0.499		0.245	
N	2744									

	Panel B 2001-2006									
Dependent Variable	**COMMREAL**		**RESREAL**		**OTHLOAN**		**OTHO**		**TRANSP**	
Intercept	0.832	***	-0.461	**	-1.362	***	0.489	**	1.500	***
L_COMP	0.019		0.012	**	-0.005		0.014		-0.017	***
L_INSID	0.031		-0.002		-0.010		0.000		-0.018	
L_INST	-0.002		0.011	*	-0.010	*	0.004		-0.002	
L_BI	-0.004		0.008	***	-0.011	***	0.008	***	-0.001	
LIQ	-0.066	***	-0.060	***	-0.024	***	0.091	***	0.059	***
CAP	0.763	***	-0.936	***	0.313	***	-0.290	**	0.199	
NPL	-2.403	**	1.492	**	9.437	***	-3.835	***	-4.797	***
LN(TA)	-0.041		0.094	***	0.162	***	-0.047	*	-0.169	***
SQLN(TA)	0.000		-0.003	***	-0.004	***	0.002	**	0.005	***
Year Dummies: Yes										
Dist. Dummies: Yes										
R-Square	0.555		0.378		0.506		0.513		0.353	
N	1425									

	Panel C 2007-2009									
Dependent Variable	**COMMREAL**		**RESREAL**		**OTHLOAN**		**OTHO**		**TRANSP**	
Intercept	0.728		-0.084		-0.413	*	0.203		0.599	***
L_COMP	0.004		-0.055	***	0.065	***	-0.005		-0.006	
L_INSID	0.006		-0.097	***	0.033		-0.010		0.074	***
L_INST	0.059	***	0.000		-0.059	***	0.000		0.004	
L_BI	-0.003		0.004	**	-0.008	***	0.006	***	0.001	
LIQ	-0.021	***	-0.048	***	-0.111	***	0.149		0.032	***
CAP	-0.102		-0.589	***	0.360	**	0.112		0.192	**
NPL	-0.111		-0.974	***	1.673	***	-0.793	***	0.159	*
LN(TA)	-0.063	**	0.042	**	0.105	***	-0.015		-0.072	***
SQLN(TA)	0.001	*	-0.001	*	-0.003	***	0.001		0.002	***
Year Dummies: Yes										
Dist. Dummies: Yes										
R-Square	0.704		0.33		0.646		0.56		0.182	
N	1319									

The same coefficients on insider ownership should be negative. As expected, the results for the full sample and the boom period indicate that more aggressive corporate governance leads to higher investments in residential loans and other opaque assets, and lower investments in transparent assets. Corporate governance seems to have little effect, however, on commercial real estate.

Previous research has documented a strong correlation between opaque assets and systematic risk. We confirm this relationship for our bank sample by regressing phi on asset composition. As expected, the results in Table 6 over the full sample show that commercial real estate, residential real estate, other loans, other opaque assets are all positively correlated with phi while transparent assets are negatively correlated.

We are interested in capturing the marginal effects of corporate governance on systematic risk. To do so, we use a 2SLS procedure where we first regress asset composition on corporate governance. Those results are in Table 5. In the second stage, we regress phi on the predicted asset composition from the first stage. The second-stage results are in Table 7.

Full sample results show that the predicted residential loans and other loans increase systematic risk, but commercial real estate loans and other opaque assets reduce systematic risk.

We are also interested in capturing the marginal effects of corporate governance on systemic risk. The first set of results in Tables 8 and 9 use the skewness ratio as the measure of systemic risk. Table 8 regresses the skewness ratio on banks' asset composition. We expect opaque assets to be correlated with a left-hand skew so that the coefficients are negative. Indeed all the asset composition variables except transparent assets are negative for the full sample.

Table 6: Regressions of Φ on Bank Assets

The dependent variable is Φ, the log-transformed R-square. All other variables are defined as in previous tables. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	**Φ**					
	Heteroskedasticity-Consistent WLS					
	2001-2009		**2001-2006**		**2007-2009**	
Intercept	-44.745	***	-45.373	***	-46.510	
COML	0.190	**	0.222	**	0.059	
RESL	0.196	*	0.206		0.084	
OTHL	0.700	***	0.286	*	0.528	***
OTHO	0.190	**	-0.128		-0.108	
TRANSP	-0.504	***	-0.174		-0.563	**
LIQ	-0.001		0.000		0.003	
NPL	2.400	***	1.728	***	2.125	***
CAP	-9.409	***	-18.477	***	-12.044	***
LN(TA)	4.950	***	4.984	***	5.114	***
SQLN(TA)	-0.137	***	-0.140	***	-0.139	***
Year Dummy: Yes						
District Dummy: Yes						
N	6692		4526		2166	
Adj R-Sq	0.42		0.43		0.45	

Table 7: Regressions of Φ on Predicted Bank Assets

This table is the second-stage regression of Φ on predicted values of opacity measurements computed from the regression in Table 5. Φ is the log-transformed R-square of stock return explained by market return in CAPM that applies the three-factor Fama-French (1992). All other variables are defined as in previous tables. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	**Φ**					
	Panel A 2001-2009		**Panel B 2001-2006**		**Panel C 2007-2009**	
Intercept	-7.893	***	-1.658		-18.541	***
COML	-0.859	***	-0.954	**	1.521	***
RESL	1.101	***	1.265	***	0.360	
OTHL	1.432	***	-0.289		0.235	
OTHO	-0.962	**	-1.322	***	0.905	
TRANSP	-0.712		1.301		-3.020	**
LIQ	0.254	***	0.036		0.047	
CAP	5.800	***	2.611		5.025	***
NPL	-14.902	***	-7.797		-12.189	***
LN(TA)	0.722	***	0.046		1.875	***
SQLN(TA)	-0.019	***	-0.001		-0.049	***
Year Dummies: Yes						
Dist. Dummies: Yes						
Adj R-Sq	0.12		0.17		0.28	

Table 8: Regressions of Skewness ratio on Bank Assets

Skewness ratio is defined as the ratio of each bank holding company's return skewness to the market return skewness by quarter. All other variables are defined as in previous tables. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	**Skewness Ratio**					
	Heteroskedasticity-Consistent WLS					
	2001-2009		**2001-2006**		**2007-2009**	
Intercept	-0.021		3.404		-5.198	
COML	-0.366		0.290		-0.913	
RESL	-1.408	**	-1.124	**	-1.639	**
OTHL	-1.891		0.888		0.727	
OTHO	-0.802	**	-0.811		-0.795	
TRANSP	0.684		0.757		0.794	
LIQ	0.002		0.002		0.006	
NPL	0.699		0.577		0.316	
CAP	-9.753	*	-9.470		-12.356	**
LN(TA)	-0.079		-0.590		0.659	
SQLN(TA)	0.003		0.020		-0.020	
Year Dummy: Yes District Dummy: Yes						
N	6692		4526		2166	
Adj R-Sq	0.06		0.08		0.16	

Table 9 captures the marginal effects of corporate governance on skewness. The table reports the second stage regression of skewness on predicted asset composition, which comes from the first-stage regressions in Table 5. The results are mixed. First, none of the coefficients is statistically significant. Second, the coefficient on residential loans is positive, opposite of what we would expect.

We also measure systemic risk with M3T, the cross-default correlation of each. Table 10 regresses M3T on bank asset composition. We expect coefficients on the opaque assets to be positive, which they are with the exception of commercial real estate.

The marginal effects from corporate governance on cross-default correlation are captured by a second-stage regression of M3T on predicted asset values estimated from Table 5. The results are mixed with the coefficient on commercial real estate positive and significant, but the coefficient on residential real estate negative and insignificant. In sum, the results fail to show a strong relationship between corporate governance and systemic risk.

E. Conclusion

This paper examines the chain effect of bank corporate governance on the choice of bank opacity, which then affects systematic risk and systemic risk. We find that a bank's asset choice including investments in opaque assets are influenced by corporate governance mechanism such as managerial incentive design, inside ownership, and board structures; and the asset choices made by managers under the influence of corporate governance in turn have an impact on the systematic risk borne by investors and the systemic risk borne by the society. Two main results are found in this essay. First, bank influenced by corporate governance. Specifically, banks with higher percentage of executive stock-based compensation, lower insider ownership, lower percentage of block-holder ownership, and more effective boards, are more likely to invest in

Table 9: Regressions of Skewness ratio on Predicted Bank Assets

This table shows the second stage regression of the skewness ratio on predicted values of opacity measurements from the regression results in Table 2.5. The skewness ratio is defined as the ratio of each bank holding company's return skewness to the market return skewness by quarter. All other variables are defined as in previous tables. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	**Skew_Ratio**		
2nd stage of 2SLS	**Panel A 2001-2009**	**Panel B 2001-2006**	**Panel C 2007-2009**
Intercept	-1.986	3.801	1.585
COML	-2.001	-3.810	1.119
RESL	4.138	4.352	4.878
OTHL	-1.216	0.363	-2.236
OTHO	-1.829	0.394	-6.769
TRANSP	0.909	-1.299	3.008
LIQ	-0.040	-0.240	0.822
CAP	-7.258	-9.931	-0.621
NPL	-10.357	-49.410	-11.465
LN(TA)	0.370	-0.107	-0.074
SQLN(TA)	-0.010	0.003	0.002
Year Dummy: Yes			
District Dummy: Yes			
N	2744	1425	1319
Adj R-Sq	0.05	0.05	0.13

Table 10: Regressing M3T_CORR on Bank Assets

M3T_CORR is the asset weighted correlation composite of each bank's third moment of OLS residual (M3T) with all other banks in the sample. All other variables are defined as in previous tables. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	M3T_CORR					
	Heteroskedasticity-Consistent WLS					
	2001-2009		2001-2006		2007-2009	
Intercept	1.248		1.621		1.548	***
COML	-0.024		0.017		-0.058	
RESL	0.118	***	0.120	***	0.091	***
OTHL	0.027	*	-0.093		0.050	**
OTHO	0.110	*	0.116		-0.051	
TRANSP	0.044		-0.073		-0.033	
LIQ	0.016	***	0.014	**	0.026	***
NPL	0.006		0.062		-0.157	*
CAP	-0.565	***	-3.490	***	-0.526	**
LN(TA)	-0.193	***	-0.246	***	-0.226	***
SQLN(TA)	0.008	***	0.009	***	0.008	***
Year Dummy: Yes District Dummy: Yes						
N	6692		4526		2166	
Adj R-Sq	0.33		0.40		0.38	

Table 11: Regressing M3T_CORR on Predicted Bank Assets

This table is the second-stage regression of M3T_CORR on predicted values of bank assets derived from Table 2.5. M3T_CORR is the asset weighted correlation composite of each bank's third moment of OLS residual (M3T) with all other banks in the sample. All other variables are defined as in previous tables. *, **, ***denote statistical significance of at the 0.1, 0.05, and 0.01 level respectively.

Dependent Variable	M3t_corr					
2nd stage of 2SLS	Panel A 2001-2009		Panel B 2001-2006		Panel C 2007-2009	
Intercept	1.859	***	3.226	***	1.208	***
COML	0.335	***	0.308	***	0.201	**
RESL	-0.045		0.024		-0.021	
OTHL	0.140		-0.124		0.025	
OTHO	0.237	***	0.325	***	-0.059	
TRANSP	-0.387	***	-0.485	***	-0.147	
LIQ	0.015		0.020		0.023	
CAP	0.684	***	1.366	***	0.023	
NPL	0.705	*	-8.658	***	-0.228	
LN(TA)	-0.281	***	-0.453	***	-0.189	***
SQLN(TA)	0.010	***	0.016	***	0.007	***
Year Dummy: Yes						
District Dummy: Yes						
Obs	2744		1425		1319	
Adj R-Sq	0.37		0.41		0.13	

opaque assets and to take higher level of risks. Secondly, bank opacity is endogenously influenced by corporate governance. Specifically, banks with higher percentage of executive stock-based compensation, lower insider ownership, lower percentage of block-holder ownership, and more effective boards, are more likely to invest in opaque assets and to take higher level of risks.

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Do Credit Rating Agencies Sacrifice Timeliness by Pursuing Rating Stability? Evidence from Equity Market Reactions To *CreditWatch* Events

A. Introduction

One of the most surprising events during the 2007-2008 financial crisis was the filing of Chapter 11 bankruptcy by Lehman Brothers, an investment bank with a 158-year history, on Monday, September 15th, 2008. The news of Lehman's collapse shook financial markets world-wide, including a drop in the Dow Jones Industrial Average of more than 500 points. The collapse of Lehman took many investors by surprise because as recently as September 12th, the previous Friday, Lehman Brothers' bonds were rated "A", an investment grade.

Though unique in its impact on global markets, the precipitous fall of Lehman from investment grade status directly to bankruptcy is not unprecedented. Several other high-profile bankrupt companies, including Enron, also maintained investment-grade ratings until just days before the bankruptcy was announced. Are rating agencies too slow in adjusting ratings?

Indeed, one major criticism of credit rating agencies is the lack of timeliness in making rating changes.[18] Studies in the finance literature have shown that credit rating changes are anticipated by the equity market (Norden and Weber (2004)), the credit default swaps market (Hull, Predescu, and White (2004); Norden and Weber (2004)), the currency market and the sovereign debt market (Reinhart (2002); Sy (2004)). Thus, credit rating agencies have faced such criticism long before the 2007-2008 financial crisis.

The difficulty of rating agencies to convey timely default information to the market is a deep-rooted problem for several reasons. First, rating agencies may not have timely or accurate information on debt issuers' financial positions (Goldstein, Kaminsky, and Reinhart (2000)), or

[18] For instance, in response to the failure of Enron in December 2001, the Senate criticized credit rating agencies for not downgrading the company's debt rating soon enough. The Staff Report of the US Senate Committee on Governmental Affairs indicated that the credit agencies' monitoring and review of Enron's finances "fell below the careful efforts one would have expected from organizations whose ratings hold so much importance".

they may not use the best rating methodologies or expend maximum effort (Cheng and Neamtiu (2009)). Second, while the financial positions of rated companies are constantly changing, the change in credit ratings can only be made periodically. As a result, a lag of credit ratings in reflecting the changes in financial positions may be inevitable. Third, default probability is a continuous variable, but credit ratings, which are indications of default likelihood, are discrete. A rating agency cannot make a rating change until the financial position of a company deteriorates to the next rating level. As a result, rating changes may lag the change in bond issuer's default probability.[19]

Another reason for the slow reaction may be related to an argument put forth by rating agencies that markets expect *stable* ratings. Ratings are often used by investors and regulators as guidance for portfolio governance.[20] Frequent changes in ratings may force portfolio managers to trade securities more frequently, thereby increasing transaction costs. Frequent rating changes may also force portfolio managers to sell securities at lower prices (when they are downgraded) and to purchase at higher prices (when they are upgraded) more frequently and thus suffering more losses. Consequently, rating agencies tend to meet the market expectations by making rating changes only when a *reversal* in ratings in the near future is unlikely (Cantor (2001); Cantor and Mann (2007)). Studies in the literature also show that the policy of issuing stable

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[19] Both Moody's Investors Service and Standard & Poor's have adopted refined rating categories by adding modifiers (e.g. "+" and "-", or "1", "2", and "3") to the generic rating categories to indicate whether a bond is on the upper, middle, or lower end of the rating category. The refinement of the rating categories can be viewed as a step moving from a discrete rating system toward a continuous spectrum. So refined ratings not only reflect the default probability more precisely, they also may trigger a rating change more quickly as rating agencies do not have to wait until the financial positions of bond issuers to deteriorate (or improve) to the next broader generic rating category to make rating changes.

[20] For instance, financial institutions such as banks and pension funds are often required to hold "investment grade" bonds only in order to show their "prudence" in fund management. As a result, when a bond is downgraded to "speculative grade", they must sell the bond at a loss.

ratings allows rating agencies to focus on bond issuers' permanent, long-term and structural credit risk, rather than the short-term and temporary credit risk (Altman and Rijken (2004)).[21]

Loffler (2005), however, argues such a policy of stable ratings may lead to a lag of rating changes behind the true changes in bond issuer's default risk. While investors may have some expectation of rating stability, they also expect rating agencies to make changes in a timely fashion. If rating agencies sacrifice timeliness for the sake of stability, markets may work faster than the rating agency and price in much of information about the changing default risk of the firm before a rating change occurs. Undoubtedly, investors would benefit from timely rating changes, especially during financial crises when investors are urgently seeking new information about the default risk of a firm.

Credit rating agencies have not been insensitive to the criticism. One specific action by Standard and Poor's (S&P's) was the creation in of a service known as *CreditWatch*, which was first offered in November 1981. *CreditWatch* provides information to investors about potential changes in default risk prior to an actual change in rating. One major purpose of *CreditWatch* is to ease the tension between the market expectation of rating stability and the market demand for rating timeliness (Altman and Rijken (2006)).

When a company is listed on *CreditWatch*, it is typically listed with either a *positive* or a *negative* potential.[22] In a listing with positive potential, the rating of the company will usually be

[21] Standard & Poor's (2003) indicates that the value of its rating products is greatest "when its ratings focus on the long-term and do not fluctuate with short-term performance." Similarly, Moody's Investors Service makes rating changes "only when it believes an issuer has experienced what is likely to be an enduring change in fundamental credit worthiness" (Cantor and Mann, October 2003).

[22] Infrequently, Standard & Poor's will place a company on the *CreditWatch* list under a third category known as "developing." When a company is listed as "developing", it means the credit rating of the company is likely to be changed, but the *direction* of the change is unknown. The number of companies listed as "developing" is far less than the number of companies listed with

eventually upgraded or affirmed (i.e. unchanged), and the rating is rarely downgraded. Similarly, in a listing with negative potential, the rating of the company will usually be eventually downgraded or affirmed, and the rating is rarely upgraded. Once the rating is changed or affirmed, the listed company is delisted (removed) from the *CreditWatch* list. Unlike credit rating changes in which rating agencies convey the default risk to the market in one action (i.e. the rating change), the publication of *CreditWatch* conveys the default information to the market through two sequential actions – first through *listing*, and then through *delisting*. The listing conveys information about the direction of the rating change, and the delisting reveals the magnitude of the actual rating change. Although listing on *CreditWatch* can lead to a bond rating change, only a small fraction of all actual rating changes are preceded by a listing on *CreditWatch.*

In this study, we examine the response of equity prices of firms listed and delisted from *CreditWatch* to determine if it improves the timeliness of rating changes. We choose to examine the reaction of equity markets (instead of debt markets) because equity investors have the most to lose from default, so prices in equity markets are more sensitive to changes in default risk. Equity markets are also considerably more liquid than bond markets and the data for equity prices are readily available. Moreover, Wansley and Clauretie (1985) examine the reaction of both equity and bond markets to *CreditWatch* events, and conclude that bond markets are considerably less efficient than equity markets.

Despite its intended purpose of informing investors of a potential rating change in a timely fashion, we find that *CreditWatch* does not completely achieve this goal. We report three empirical results in support of this conclusion. First, we find equity markets experience

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positive or *negative* potentials. We do not include bonds listed as “developing” in our study.

substantial positive (negative) reaction to the listing of companies with positive (negative) potential on *CreditWatch prior* to the actual date of listing. Second, equity markets exhibit little reaction to the delisting of a company from *CreditWatch*, even when the delisting is accompanied by a change in rating. Third, we find that the pre-listing abnormal returns in equity markets are good predictors of both the direction and the magnitude of the eventual change in credit rating. Collectively, our findings suggest that rating agencies may sacrifice timeliness for the sake of stability and that even *CreditWatch*, which is designed to mitigate the disadvantage caused by stable rating policies, is not a completely effective instrument.

The remainder of the paper is organized as follows. Section I discusses the data and the methodology. Section II presents the empirical analyses and results, and Section III concludes.

B. Data and Methodology

B.1 Sample Construction and Description

Our sample construction begins with firms placed on *CreditWatch* between January 2002 and December 2005. We hand-collect the following data: 1) company name, 2) listing date, 3) existing S&P senior debt rating, 4) listing potential, and 5) new S&P senior debt rating after delisting. From this group, we exclude all firms with insufficient data from the Center in Research and Security Prices (CRSP) to compute abnormal returns surrounding the listing date. We also exclude firms for which definitive information about the action taken by S&P regarding the firms' rating upon delisting is unavailable. The final sample consists of 604 observations, with 101 listed with "positive" potential, 503 listed with "negative" potential.[23] The sample

[23] There is one (five) extremely rare cases in which firms were listed with positive (negative) potentials but were downgraded (upgraded). We report these observations in our descriptive statistics, but exclude them from further analysis.

composition is consistent with similar studies in the literature (e.g. Dichev and Piotroski (2001); Hand, Holthausen, and Leftwich (1992); Holthausen, and Leftwich (1986)) in that downgrades are considerably more common than upgrades.

Following Morgan (2002), we transform letter ratings into a numerical scale with higher quality ratings transformed into lower numbers. The details of the transformation are provided in Appendix I. Tables 1 and 2 report the frequency distributions of the initial rating and the new rating upon delisting for companies listed with “positive” and “negative” potentials, respectively. For listings with positive potential, approximately 80% of firms are upgraded when delisted from *CreditWatch*. For firms listed with negative potential, approximately 60% are downgraded when delisted.

Table 3 reports basic financial characteristics of the firms in the sample categorized by type of listing. Financial data is obtained from Compustat for the year preceding the date of listing. The sample sizes are reduced slightly because of missing data in Compustat. Statistically significant differences exist regarding the size of the companies (measured by total assets) and the cash ratio. Specifically, firms listed with negative potential are larger in size and have lower cash ratios compared to firms listed with positive potential. Firms listed with positive potential tend to remain on the *CreditWatch* list longer than those listed with negative potential, but the difference is not statistically significant. A breakdown of the number of firms by the first digit of the Compustat SIC code is provided in Appendix II.

B.2 Methodology

To capture the reaction of the equity market, we employ an event study methodology by computing daily abnormal returns (AR) and cumulative abnormal returns (CAR) of the companies in event windows surrounding the listing and delisting dates. For robustness, we

Table 1: Summary of *CreditWatch* Listings with Positive Potential

This table summarizes the frequency distribution by ratings of companies that were listed on the *CreditWatch* with "positive" potential between January 2002 and December 2005. The credit ratings on the very left column are the original ratings of companies immediately before the *CreditWatch* listing. The ratings on the top row are the new ratings after the removal (delisting) from the *CreditWatch* list. Ratings on the diagonal are companies whose ratings remain unchanged. Since this table contains only firms listed with "positive" potential, all the companies ended with rating upgrades (below the diagonal) or unchanged (on the diagonal) except one company (which was lowered from B+ to B-).

		Rating After Delisting																					
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	Total
Original Rating Before Listing	AAA	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	AA+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	AA-	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	A+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	A-	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
	BBB+	0	0	1	1	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	10
	BBB	0	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	7
	BBB-	0	0	0	0	0	0	1	1	9	0	0	0	0	0	0	0	0	0	0	0	0	11
	BB+	1	0	0	0	0	0	1	0	0	4	3	0	0	0	0	0	0	0	0	0	0	9
	BB	0	0	0	0	0	0	0	0	0	3	3	3	0	0	0	0	0	0	0	0	0	9
	BB-	0	0	0	0	1	0	0	1	0	0	0	9	3	0	0	0	0	0	0	0	0	14
	B+	0	0	0	0	0	0	0	0	0	0	0	3	9	3	0	1	0	0	0	0	0	16
	B	0	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	0	0	0	0	5
	B-	0	0	0	0	0	1	0	0	0	0	0	0	2	3	2	1	0	0	0	0	0	9
	CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	3
	CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	CCC-	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
	CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
	C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Total	1	0	2	1	2	4	9	11	9	7	6	16	15	11	2	4	0	0	0	1	0	101

Table 2: Summary of *CreditWatch* Listings with Negative Potential

This table summarizes the frequency distribution by ratings of companies that were listed on the *CreditWatch* with "negative" potential between January 2002 and December 2005. The credit ratings on the very left column are the original ratings of companies immediately before the *CreditWatch* listing. The ratings on the top row are the new ratings after the removal (delisting) from the *CreditWatch* list. Ratings on the diagonal are companies whose ratings remain unchanged. Since this table contains only firms listed with "negative" potential, with the exception of five cases, all the companies ended with rating downgrades (above the diagonal) or unchanged (on the diagonal).

	Rating After Delisting																						
Original Rating Before Listing	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	D	Total
AAA	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
AA+	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
AA	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
AA-	0	0	0	3	8	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13
A+	0	0	0	0	6	9	6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22
A	0	0	0	0	0	9	18	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	30
A-	0	0	0	0	0	0	21	11	3	0	0	1	0	0	0	0	0	0	0	0	0	0	36
BBB+	0	0	0	0	0	0	0	17	14	4	1	1	0	0	0	0	0	0	0	0	0	0	37
BBB	0	0	0	0	0	0	0	0	20	23	5	2	0	0	0	0	0	0	0	0	0	0	50
BBB-	0	0	0	0	0	0	0	0	0	25	26	9	4	0	0	0	0	0	0	0	0	0	64
BB+	0	0	0	0	0	0	0	0	0	1	11	20	2	3	1	0	0	0	0	0	0	0	38
BB	0	0	0	0	0	0	0	0	0	0	0	19	28	11	1	1	0	0	0	0	0	0	60
BB-	0	0	0	0	0	0	0	0	0	0	0	0	21	21	4	3	0	0	0	0	0	0	49
B+	0	0	0	0	0	0	0	0	0	0	0	0	0	20	12	4	0	1	0	1	0	0	38
B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	3	7	3	0	1	0	0	23
B-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	3	0	2	0	0	0	9
CCC+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	0	0	5
CCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	2	0	1	5
CCC-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	3	5
CC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	2	0	4	9
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	0	3	3	5	15	19	46	32	38	53	43	52	55	55	27	16	12	6	7	8	0	8	503

Table 3: Financial Characteristics of Firms Listed on CreditWatch

This table presents basic financial characteristics of the sample firms for the year prior to being listed on *CreditWatch*. Total Assets are presented in millions of dollars. ROA is computed as net income divided by total assets. The Debt Ratio is computed as total liabilities divided by total assets. The Cash Ratio is cash and cash equivalents divided by total assets. The days between listing and delisting is the number of calendar days between the listing and delisting dates. *, **, *** denotes statistically different from zero based on a standard t-test for the means and a Wilcoxon test for the medians at the 10%, 5% and 1% levels, respectively.

		Total Assets ($MM)	ROA (%)	Debt Ratio (%)	Cash Ratio (%)	Days Between Listing and Delisting
		Firms with Positive Potentials				
	Mean	12,754	-4.05%	72.87%	10.90%	116.2
Percentile	5th	461	-33.61	31.52	0.97	16.0
Percentile	25th	1,387	-1.92	55.77	3.30	36.0
Percentile	Median	3,171	1.80	71.22	7.45	96.5
Percentile	75th	10,623	5.42	88.82	12.04	157.5
Percentile	95th	63,667	10.60	109.67	31.64	291.0
	Std. Dev.	22,298	32.82	29.09	12.22	91.2
	N	97	97	97	97	100
		Firms with Negative Potentials				
	Mean	25,600	-0.47%	69.60%	8.60%	102.1
Percentile	5th	611	-22.41	39.71	0.34	22.0
Percentile	25th	2,074	-2.35	55.81	1.76	44.0
Percentile	Median	6,143	1.69	67.83	4.74	73.5
Percentile	75th	16,604	4.56	82.37	11.44	134.0
Percentile	95th	103,914	11.31	102.08	28.31	275.0
	Std. Dev.	83,588	12.64	19.86	10.73	88.3
	N	486	486	486	486	498
	Difference of Means	-12,846***	-3.58	3.27	2.30*	14.1
	Difference of Medians	-13,433***	0.11	6.66	2.71***	23.0

consider three estimation procedures – the market model, market adjusted return model, and the Fama-French (1992) model – to calculate the abnormal returns. The market index is the CRSP value-weighted index and the daily Fama-French factors are also obtained from CRSP. The estimation period is the 200 trading days ending 61 trading days prior to the event date. The market model is specified as a single factor model with the rate of return of a common stock as a function of the return of a market index:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \qquad (1)$$

Where R_{jt} is the rate of return of the common stock of firm j on day t; R_{mt} is the rate of return of a market index on day t; ε_{jt} is the error term -- a random variable that, by construction, must have an expected value of zero, and is assumed to be uncorrelated with R_{mt}. The coefficient β_j is a parameter that measures the sensitivity of R_{jt} to the market index.

Market model abnormal return (or prediction error) for the common stock of the firm j on day t, AR_{jt} is defined as:

$$AR_{jt} = R_{jt} - (\hat{\alpha}_j + \hat{\beta}_j R_{mt}) \qquad (2)$$

where the coefficients $\hat{\alpha}_j$ and $\hat{\beta}_j$ are ordinary least squares estimates of α_j and β_j.

The market adjusted return model computes abnormal returns by simply subtracting the observed return on the market index from the rate of return of the common stock:

$$AR_{jt} = R_{jt} - R_{mt} \qquad (3)$$

The Fama-French (1992) three-factor model states that security prices are determined by three factors, defined as:

$$ER_{jt} = \alpha_j + \beta_j ER_{mt} + S_j SMB_t + h_j HML_t + \varepsilon_{jt}. \qquad (4)$$

where ER_{jt} is the excess rate of return of the common stock beyond the risk-free rate of firm j on day t; ER_{mt} is the excess return of the market index beyond the risk-free rate on day t; SMB_t is the average return on small market-capitalization portfolios minus the average return on three large market-capitalization portfolios; HML_t is the average return on two high book-to-market equity portfolios minus the average return on two low book-to-market equity portfolios; ε_{jt} is the error term. The abnormal return (or prediction error) for the common stock of firm j on day t is computed as:

$$AR_{jt} = ER_{jt} - (\hat{\alpha}_j + \hat{\beta}_j ER_{mt} + \hat{s}_j SMB_t + \hat{h}_j HML_t) \qquad (5)$$

Cumulative abnormal returns are the sum of daily abnormal returns over a specified time period. For all three models, the CAR from trading day T_1 through T_2 is computed for firm j as:

$$CAR_{j,(T_1 T_2)} = \sum_{t=T_1}^{T_2} AR_{jt} \, . \qquad (6)$$

where T_1 and T_2 are the beginning and ending days of the event window, respectively.

C. Empirical Results

Our goal in this paper is evaluating the ability of *CreditWatch* to convey information to markets in a timely fashion. Accordingly, we examine the equity market's reaction to both the listing on and delisting from *CreditWatch.* We also examine to what extent the rating action that occurs upon delisting (i.e. an affirmed rating or a change in rating) is reflected in the abnormal returns.

C.1 Equity Market Reaction to CreditWatch Listing

To assess whether *CreditWatch* listings reflect the changes of the listed companies' financial positions in a timely fashion, we calculate the daily AR on days surrounding the date of listing and the CAR for several event windows. For robustness, we use three different return generating models, as described in the previous section. Separate results of the mean values for listings with positive and negative potential are presented in Table 4.

Analysis of the daily AR shows a significant positive (negative) reaction by the market on the day of a listing (Day 0) with positive (negative) potential. Taken alone, this finding suggests that a listing on *CreditWatch* provides the market with new information. However, the magnitude of the reaction on the day of listing is often substantially smaller than the CAR present in the days prior to the listing date, suggesting the listing on *CreditWatch* is somewhat delayed. This trend is particularly pronounced for those firms listed with negative potential. For example, the market adjusted model abnormal return on Day 0 is -2.84%, but $CAR_{(-30,-1)}$ is nearly three times as large at -8.20%.

Although the abnormal returns are both statistically and economically significant on the listing day, we cannot conclude whether the return on the listing day was due to the announcement of the *CreditWatch* list, or it is part of the continuing adjustment process that may have started as early as 60 days before the listing. Even if the significant abnormal return on the listing day is entirely related to the announcement of the listing, the results still indicate the placement of firms on *CreditWatch* may not be timely enough. Regardless of the specification for computing abnormal returns (the market model, market adjusted return model, or the Fama-French model), the results in Table 4 suggest that equity markets have reflected a substantial portion of the change in listed firms' financial positions *before* the listing day. For robustness, we also examine the median values of the daily AR and CAR, and the results (unreported) confirm the findings of the analysis using the value of the means.

We next examine the equity market reaction surrounding the listing date categorized by the delisting action. We classify the listed companies into four categories based on the magnitude of the actual change in rating that occurs on the delisting day. The four categories are: no rating change (i.e. rating being affirmed), a small rating change (changed by one notch), a medium rating change (changed by two notches), and a large rating change (changed by three notches or more). The subcategories are further separated for companies listed with positive and negative potential, creating a total of eight possible categories.

The mean daily AR and CAR over various event windows surrounding the listing date for each category are presented in Table 5. To conserve space, we report only the results from the market model estimation throughout the remainder of the paper, but both the market adjusted return model and the Fama-French models produces results qualitatively similar to those from the market model.

The results in Table 5 provide considerable evidence suggesting a positive correlation between the magnitude of the CARs prior to the listing day and the magnitude of the rating changes announced on the delisting day. For positively listed companies, the magnitude of the CARs prior to the listing day does not monotonically increase with the magnitude of rating changes, but we find the average magnitude of the CARs for companies within the two smallest rating change categories (i.e. companies whose ratings were affirmed or were changed by one notch) are smaller than the CARs for companies with two larger rating change categories (i.e. companies whose ratings were changed by two notches or three notches or more).

For companies listed with negative potentials (which is a much larger sample compared to the listings with positive potential), the evidence is much stronger. The magnitude of the CAR prior to the listing, regardless of the event window, exhibits a consistent monotonic trend. This is strong evidence that equity markets have anticipated *prior* to the listing date not only

Table 4: Equity Market Reaction to CreditWatch Listing

This table presents the mean values of the daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the listing day on *CreditWatch*. Results are presented separately based on the expected rating change potential (positive or negative) at the time of listing. The AR and CAR are calculated using three models as described in Section I: the market model (MKT), the market adjusted return model (MADJ), and the Fama-French 3-factor model (FF). *, **, *** denotes statistically different from zero based on a Patell z-test at the 10%, 5% and 1% levels, respectively.

AR	Firms with Positive Potentials						Firms with Negative Potentials					
Day	MKT Model		MADJ Model		FF Model		MKT Model		MADJ Model		FF Model	
-7	0.08%		0.26%		0.11%		-0.28%	**	-0.31%	**	-0.26%	
-6	-0.07%		-0.01%		-0.11%		-0.32%	***	-0.38%	***	-0.32%	***
-5	0.15%		0.39%		0.09%		-0.76%	***	-0.77%	***	-0.69%	
-4	0.34%	*	0.43%	**	0.36%		-0.24%	*	-0.32%	**	-0.24%	
-3	0.78%	***	0.78%	***	0.70%	**	-0.21%	*	-0.24%	*	-0.21%	***
-2	0.20%	**	0.34%	***	0.11%	**	-0.75%	***	-0.82%	***	-0.68%	**
-1	-0.10%		0.13%		-0.12%		-1.41%	***	-1.46%	***	-1.40%	***
0	2.71%	***	2.79%	***	2.67%	**	-2.83%	***	-2.84%	***	-2.86%	***
1	0.18%		0.27%		0.26%	*	-1.14%	***	-1.18%	***	-1.11%	***
2	0.01%		0.09%		0.03%		-0.24%	**	-0.26%	**	-0.27%	**
3	-0.05%		0.03%		0.01%		0.25%	*	0.20%		0.28%	
CAR	**Firms with Positive Potentials**						**Firms with Negative Potentials**					
Days	**MKT Model**		**MADJ Model**		**FF Model**		**MKT Model**		**MADJ Model**		**FF Model**	
(-60, -1)	3.78%	***	10.01%	***	2.89%	**	-7.11%	***	-10.82%	***	-7.08%	***
(-30, -1)	1.64%	**	4.85%	***	1.37%	*	-6.23%	***	-8.20%	***	-5.95%	***
(-7,-1)	1.39%	***	2.32%	***	1.16%		-3.97%	***	-4.32%	***	-3.80%	***
(0,0)	2.71%	***	2.79%	***	2.67%	**	-2.83%	***	-2.84%	***	-2.86%	***
(+1,+3)	0.13%		0.40%		0.29%		-1.13%	***	-1.24%	***	-1.10%	**
N	101		101		101		503		503		503	

theCreditWatch listing potential (positive or negative), but also the change in rating at delisting. This point is well-illustrated in Figure 1, which plots $CAR_{(-7,+3)}$ for the eight categories. Despite some notable reaction on the day of announcement, the adjustment process in equity prices begins well before then, particularly for listings that ultimately result in rating changes of at least two notches. The results suggest that *CreditWatch* is still not timely enough in conveying the

Table 5: Equity Market Reaction to CreditWatch Listing Categorized by Delisting Action

This table presents the mean values of daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the listing date on *CreditWatch* categorized by the change in rating that occurs when the firm is delisted. The AR and CAR are computed using the market model as described in Section I. The sample size is reduced because firms delisted with rating changes in an opposite direction of the initial listing are excluded from analysis. Separate results are presented for firms listed with positive and negative potential. Within the categories of positive (negative) potential, results are further classified by the magnitude of delisting action: affirmed with no change in rating, up (down) by one notch, up (down) by two notches, or up (down) by three or more notches. Abnormal returns generated by both the market adjusted return model and Fama-French 3-factor model produce qualitatively similar results and are not reported. *, **, *** denotes statistically different from zero based on a Patell z-test at the 10%, 5% and 1% levels, respectively.

AR	**Positive**								**Negative**							
Day	**Affirmed**		**Up 1 Notch**		**Up 2 Notches**		**Up 3+ Notches**		**Affirmed**		**Down 1 Notch**		**Down 2 Notches**		**Down 3+ Notches**	
-7	0.66%		0.14%		-0.17%		-0.76%		-0.07%		-0.25%	*	-0.88%	**	-0.21%	
-6	-0.32%		-0.12%		-0.55%		0.77%		-0.29%	**	-0.12%		-1.53%	***	0.39%	
-5	-0.06%		0.09%		0.90%	*	0.16%		-0.13%		-0.86%	***	-1.61%	***	-1.18%	*
-4	0.02%		0.01%		2.42%	***	0.35%		-0.02%		-0.46%	***	-0.03%		-0.23%	
-3	0.55%		0.34%	*	3.91%	***	0.31%		0.14%		-0.29%	**	-0.34%		-1.13%	
-2	-0.24%		0.00%		-0.42%		1.75%	***	-0.54%	***	-0.17%	**	-1.13%	***	-4.17%	***
-1	0.19%		-0.68%	*	1.41%	***	0.49%		-0.87%	***	-1.74%	***	-1.05%	***	-3.20%	***
0	4.84%	***	0.07%	**	4.24%	***	8.94%	***	-0.65%	**	-3.74%	***	-2.89%	***	-8.63%	***
1	0.48%		0.17%		-0.11%		0.00%		-0.78%	***	-0.80%	***	-1.43%	***	-3.95%	***
2	-0.14%		-0.18%		1.34%	**	0.04%		-0.29%		-0.45%	***	-0.30%		0.95%	
3	-0.77%		0.22%		0.23%		-0.30%		0.07%		0.03%		0.53%	*	1.51%	**
CAR	**Positive**								**Negative**							
Day	**Affirmed**		**Up 1 Notch**		**Up 2 Notches**		**Up 3+ Notches**		**Affirmed**		**Down 1 Notch**		**Down 2 Notches**		**Down 3+ Notches**	
(-60, -1)	7.53%	*	-0.48%		11.02%	***	6.36%	*	-1.83%	***	-7.68%	***	-12.66%	***	-23.69%	***
(-30, -1)	5.53%		-1.94%		9.84%	***	3.01%		-2.08%	***	-7.09%	***	-10.70%	***	-18.20%	***
(-7,-1)	0.80%		-0.23%		7.51%	***	3.07%	**	-1.78%	***	-3.88%	***	-6.58%	***	-9.72%	***
(0,0)	4.84%	***	0.07%	**	4.24%	***	8.94%	***	-0.65%	**	-3.74%	***	-2.89%	***	-8.63%	***
(+1,+3)	-0.44%		0.21%		1.46%		-0.26%		-0.99%	***	-1.22%	***	-1.19%	**	-1.50%	***
N	20		55		11		14		193		199		68		38	

information about the change of financial positions of listed firms to the market.

C.2 Equity Market Reaction to CreditWatch Delisting

Having provided evidence that the magnitude of the rating change at delisting is reflected in equity prices *prior* to the listing announcement, we next examine the information content of the delisting event by computing the AR and CAR surrounding the date of delisting. Table 6 presents the daily AR and CAR over various event windows surrounding the delisting date by the type of action that occurs when the company is delisted from *CreditWatch*. We take care to ensure that none of the pre-delisting windows overlap with post-listing windows. The results in Table 6 are noticeably different from those presented in Table 5 for the listing date, as there is very little market reaction on the day of the delisting announcement (Day 0). This is true regardless of whether the firm was listed with positive or negative potential, and also irrespective of the magnitude of the rating change upon delisting. The results suggest that the announcement of delisting (in which the actual rating changes are made) contains limited information. *C.3 Predicting the Change in Rating*

We have shown equity markets experience significant reactions in the days *prior* to a firm's listing day. We have also shown markets exhibit little reaction on the day a firm is delisted from *CreditWatch*. We now examine whether the pre-listing equity market reaction is an effective predictor of the eventual change in rating upon delisting. If it is, then *CreditWatch* is too slow in reflecting the changes in the firms' financial positions.

While the results in Table 5 and Figure 1 suggest that pre-listing CARs may serve as good predictors of rating changes, we now provide additional statistical support. To ascertain the degree of statistical significance, we regress the magnitude of the rating change at delisting on the CARs from the listing period using OLS estimation. Recall that higher rated bonds receive lower numerical scores, so an upgrade (downgrade) results in a negative (positive) value for the dependent variable. The results for several specifications of this model are presented in Table 7.

Model 1 contains only the CARs from the listing period as independent variables.[24] The CARs for both the pre-listing (LIST_CAR (-7,-1)) and listing date (LIST_CAR(0,0)) are negative and statistically significant, and an F-test for the equality of coefficients shows that the magnitude of the listing date CAR is significantly greater. This suggests that the announcement day contains significantly more information than the pre-listing period. However, the inclusion of additional control variables eliminates this statistical difference.

Model 2 adds control variables for the time between the listing and delisting dates (SPAN) and the initial numerical rating at the time of listing (LIST_RATING). We also include dummy variables to control for proximity to the threshold between investment-grade and speculative-grade (junk) status. A bond rating of BB+ and below is considered junk status. Prior research (e.g. Brister, Kennedy, and Liu (1994); Jorion and Zhang (2007)) has demonstrated movement into or out of junk status has a more pronounced impact on markets since many institutional investors are prohibited from holding junk bonds. NEAR_JUNK takes a value of one for *negatively* listed firms with an initial rating of BBB+, BBB, or BBB-. NEAR_JUNK bonds are most likely to be downgraded into the junk bond categories upon delisting. Similarly, NEAR_INVESTMENT takes a value of one for *positively* listed firms with an initial rating of BB+, BB, or BB-. NEAR_INVESTMENT bonds are most likely to be upgraded into investment-grade categories upon delisting. The addition of these two dummy variables reduce the magnitude of LIST_CAR(0,0), but both LIST_CAR(-7,-1) and LIST_CAR(0,0) retain

[24] We also consider the CARs surrounding the delisting date as independent variables in our regression models. These variables never achieved statistical significance and appear to have no relationship with the magnitude of the rating change, so we do not report them.

Figure 1: Cumulative Abnormal Returns Surrounding the Listing Date Categorized by Delisting Action

This figure presents the mean cumulative abnormal returns (CARs) surrounding the listing date (defined at t = 0) from seven days before to three days after the listing day (-7,+3), categorized by the delisting action. POS_AFF is listed with positive potential followed by rating affirmation (i.e. unchanged) upon delisting. POS_UP1, POS_UP2, and POS_UP3+ are listed with positive potential followed by upgrade of 1, 2, and 3 or more notches, respectively, upon delisting. NEG_AFF is listed with negative potential followed by rating affirmation upon delisting. NEG_DOWN1, NEG_DOWN2, and NEG_DOWN3+ are listed with negative potential followed by downgrade of 1, 2, and 3 or more notches, respectively, upon delisting.

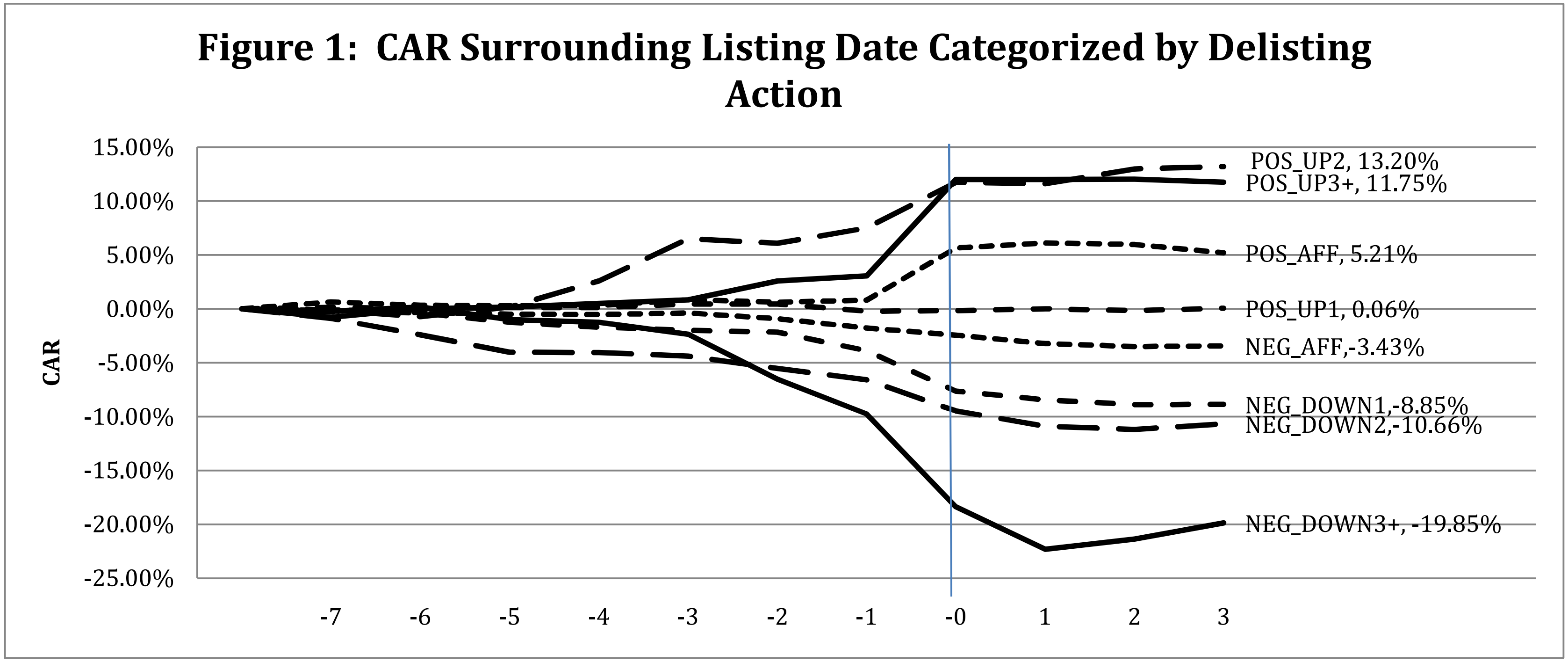

Table 6: Equity Market Reaction to CreditWatch Delisting

This table presents the mean values of daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the date of delisting from *CreditWatch*. The AR and CAR are computed using the market model as described in Section I. The sample size is reduced because firms delisted with rating changes in an opposite direction of the initial listing are excluded from analysis. Separate results are presented for firms listed with positive and negative potential. Within the categories of positive (negative) potential, results are further classified by the magnitude of delisting action: affirmed with no change in rating, up (down) by one notch, up (down) by two notches, or up (down) by three or more notches. Abnormal returns generated by both the market adjusted return model and Fama-French 3-factor model produce qualitatively similar results and are not reported. *, **, *** denotes statistically different from zero based on a standard t-test at the 10%, 5% and 1% levels, respectively.

AR	**Firms Listed with Positive Potential**				**Firms Listed with Negative Potential**			
Day	**Affirmed**	**Up 1 Notch**	**Up 2 Notches**	**Up 3+ Notches**	**Affirmed**	**Down 1 Notch**	**Down 2 Notches**	**Down 3+ Notches**
-7	-3.31% ***	-0.58%	0.23%	-1.53%	0.01%	-0.37% *	-1.49% ***	4.95% ***
-6	1.04% **	0.18% *	-0.49%	-1.66% *	0.22%	-0.42%	-2.07% ***	1.05% ***
5	-0.93% ***	-1.01% **	-0.53%	-0.98%	-0.15%	-0.13%	0.43%	-1.22% **
4	-0.34%	0.63%	0.24%	-0.55%	0.19%	0.59% *	0.33%	0.84%
3	0.10%	-0.42%	-0.38%	-0.43%	0.11%	0.57% *	-0.85% **	0.57% **
2	-0.20%	0.29%	0.18%	-1.84%	0.26%	-0.01%	0.01%	-2.98% ***
-1	-0.03%	-0.16%	-1.48% *	1.18%	0.04%	0.35% *	0.15%	-0.87%
0	-0.55%	-0.62% **	0.65%	-0.36%	0.28%	-0.07%	1.04% ***	-1.49% ***
1	0.56%	0.50% *	0.64%	0.39%	0.10%	0.16%	-0.69% **	0.94% **
2	-0.26%	1.37% *	-1.72% **	-0.46%	0.13%	0.22%	-0.24%	0.12%
3	0.07%	0.17%	-0.19%	-0.42%	0.22%	0.47% **	-1.26% **	2.29% ***
CAR	**Firms Listed with Positive Potential**				**Firms Listed with Negative Potential**			
Day	**Affirmed**	**Up 1 Notch**	**Up 2 Notches**	**Up 3+ Notches**	**Affirmed**	**Down 1 Notch**	**Down 2 Notches**	**Down 3+ Notches**
(-7,-1)	-3.66% ***	-1.07%	-2.23%	-5.82% *	0.68% *	0.59%	-3.50% **	2.35%
(0,0)	-0.55%	-0.62% **	0.65%	-0.36%	0.28%	-0.07%	1.04% **	-1.49% ***
(+1,+3)	0.37%	2.05% *	-1.27%	-0.49%	0.44%	0.85% *	-2.16% **	3.35% ***
N	19	49	8	6	191	196	63	32

Table 7: Predicting the Magnitude of Rating Change at Delisting

This table presents results of regressing rating changes at delisting on the CAR surrounding the listing date and other control variables. The dependent variable in all models is the numerical change in rating that occurs upon delisting from *CreditWatch*. An upgrade (downgrade) is reflected by a negative (positive) number. LIST_CAR(T_1,T_2) is the CAR computed using the market model from days T_1 to T_2 relative to the day listed on *CreditWatch*. SPAN is the number of days between listing and delisting. LIST_RATING is the numerical rating at the time of listing. NEAR_JUNK is a dummy variable equal to one for negatively listed firms with an initial rating of BBB+, BBB, or BBB-. NEAR_INVESTMENT is a dummy variable equal to one for positively listed firms with an initial rating of BB+, BB, or BB-. Financial variables are from the fiscal year ending prior to the listing date: LN(ASSETS) is the natural log of total assets, ROA is net income divided by total assets, DEBT_RATIO is total liabilities divided by total assets, CASH_RATIO is cash and equivalents divided by total assets. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Rating Change	Both Positive and Negative								Positive		Negative	
	(1) OLS		(2) OLS		(3) OLS		(4)OLS		(5) Tobit		(6) Tobit	
Intercept	0.426	***	0.991	***	0.993	***	1.618	***	1.905	***	-0.330	
LIST_CAR(-7,-1)	**-1.604**	***	**-1.644**	***	**-1.863**	***	**-1.515**	***	**-1.345**	***	**-1.248**	**
LIST_CAR(0,0)	**-3.006**	***	**-2.456**	***	**-2.445**	***	**-2.151**	***	**-2.076**	***	**-1.987**	***
LIST_CAR(+1,+3)	**0.177**		**0.284**		**0.282**		**0.278**		**0.171**		**-0.511**	
SPAN			-0.002	***	-0.002	***	-0.002	***	-0.002	***	-0.001	
LIST_RATING			-0.030	**	-0.031	**	-0.035	*	-0.048	**	-0.032	
NEAR_JUNK			**0.253**	**	**0.294**	**	**0.310**	**			**0.383**	***
NEAR_INVESTMENT			**-1.806**	***	**-1.837**	***	**-1.848**	***	**-2.944**	***		
LIST_CAR(-7,-1)* NEAR_JUNK					**1.660**	*	**2.066**	**			**1.271**	
LIST_CAR(-7,-1)* NEAR_INVESTMENT					**-3.033**		**-2.827**		**-1.746**			
LN(ASSETS)							-0.013		-0.009		-0.002	
ROA							-0.305		-0.312		-0.025	
DEBT_RATIO							-0.103		-0.245		-0.044	
CASH_RATIO							0.276		-0.080		0.051	
Year Dummy	No		No		No		Yes		Yes		Yes	
R-Square	0.087		0.194		0.209		0.217		0.470		0.340	
F-value	19.93	***	21.58	***	17.24	***	11.1	***				
Log Likelihood Ratio Statistics									243.96	***	1241.21	***
N	598		598		598		583		583		583	
Equality of Coefficients (F-test)	**Difference**		**Difference**		**Difference**		**Difference**		**Difference**		**Difference**	
H_0:LIST_CAR(-7,-1) = LIST_CAR(0,0)	1.402	***	0.812		0.582		0.636		0.731		0.739	

statistical significance. Model 3 includes an interaction of the dummy variables NEAR_JUNK and NEAR_INVESTMENT with LIST_CAR(-7,-1). The interaction of LIST_CAR(-7,-1) with NEAR_JUNK is positive and significant.

Model 4 adds basic financial characteristics of the listed firms as control variables. We include the natural log of assets, LN(ASSETS), as measure of size, ROA as a measure of profitability, DEBT_RATIO as a measure of leverage, and CASH_RATIO as a measure of liquidity, but none of the variables have a statistically significant impact on the magnitude of the rating change.

As a robustness check, Models 5 and 6 repeat the variable structure of Model 4, but separate the observations into categories of positive and negative potentials, respectively. Separating the sample into these two categories results in a truncation of the dependent variable (i.e. the change in rating), so we estimate Models 5 and 6 using a Tobit procedure. The results for both Models 5 and 6 are consistent with the findings in Models 1 through 4. The pre-listing and listing day CARs are statistically related to the change in rating upon delisting.

To ascertain the economic significance of our results, consider the coefficient for LIST_CAR(-7,-1) in Model 4 of -1.515. A one percentage point decline in the pre-listing CAR is associated with a rating downgrade of about 0.015 notches. At first glance this may seem trivial, but the mean pre-listing CARs from Table 5 are substantially larger than 1%. The fact that the pre-listing CARs are good predictors of rating changes upon delisting suggest that the *CreditWatch* is still too slow in reflecting the changes in firms' financial positions.

C.4 Robustness Checks

Probit Model

As a robustness check, we perform ordered probit regressions using the same variable structures as Models 1, 2 and 4 in Table 7. The results are presented in Table 8, and confirm our previous findings. Separate intercepts are reported for each magnitude of rating change. The intercept values exhibit a monotonically increasing pattern. Both LIST_CAR(-7,-1) and LIST_CAR(0,0) are again statistically significant, but of a lower magnitude relative to Table 7. This finding is not surprising given that the ordered probit procedure provides a specific intercept for each category of rating change, instead of a single intercept as in the OLS and Tobit procedures in Table 7. The usefulness of pre- listing CARs in predicting the rating changes on the delisting date once again suggests that *CreditWatch* does not reflect the changes in the listed firms' financial positions timely enough.

Initial Bond Quality

Studies in the literature (e.g. Brister, Kennedy, and Liu, 1994; Jorion and Zhang, 2007) have shown that for the same magnitude of downgrade (e.g. downgrade by one notch), the impact on a low-grade bond (e.g. from B+ to B) tends to be greater than a high-grade bond (e.g. from A+ to A) because low-grade bonds are closer to bankruptcy and they are more scrutinized by investors and regulators. As a robustness check of our on *CreditWatch*. We choose the largest category with similar rating changes, the one notch downgrades, and construct three sub-categories based on the initial rating: high ratings (A+), medium ratings (BBB), and low ratings (B+).

The results of the analysis are presented in Table 9, and demonstrate that the initial level of the rating is an important determinant of the magnitude of the CAR surrounding the *CreditWatch* results, we examine whether the same principles holds true for the CAR surrounding the listing listing date. The magnitude of CARs during the pre-listing period increases monotonically as the credit level decreases. For instance, the CARs over the period (-60, -1) are -2.19%, -8.97%, and

Table 8: Ordered Probit Model

This table presents results of an ordered probit model that regresses rating changes at delisting on the CAR surrounding the listing date and other control variables. The dependent variable in all models is the numerical change in rating that occurs upon delisting from *CreditWatch*. An upgrade (downgrade) is reflected by a negative (positive) number. LIST_CAR(T_1,T_2) is the CAR computed from days T_1 to T_2 relative to the day listed on *CreditWatch*. SPAN is the number of days between listing and delisting. LIST_RATING is the numerical rating at the time of listing. NEAR_JUNK is a dummy variable equal to one for negatively listed firms with an initial rating of BBB+, BBB, or BBB-. NEAR_INVESTMENT is a dummy variable equal to one for positively listed firms with an initial rating of BB+, BB, or BB-. Financial variables are from the fiscal year ending prior to the listing date: LN(ASSETS) is the natural log of total assets, ROA is net income divided by total assets, DEBT_RATIO is total liabilities divided by total assets, CASH_RATIO is cash and equivalents divided by total assets. ***, **, * denotes statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Rating Change	Ordered Probit (1)		Ordered Probit (2)		Ordered Probit (3)	
Intercepts:						
Down 6 Notches	-2.940	***	-2.555	***	-2.324	***
Down 5 Notches	-2.519	***	-2.141	***	-1.901	***
Down 4 Notches	-2.050	***	-1.668	***	-1.424	***
Down 3 Notches	-1.349	***	-0.961	***	-0.759	*
Down 2 Notches	-0.705	***	-0.313	*	-0.084	
Down 1 Notches	0.307	***	0.735	***	0.984	**
Affirmed	1.450	***	2.018	***	2.276	***
Up 1 Notches	2.109	***	2.794	***	3.087	***
Up2 Notches	2.387	***	3.101	***	3.390	***
Up 3 Notches	2.633	***	3.377	***	3.708	***
Up 4 Notches	2.752	***	3.519	***	3.884	***
Up5 Notches	2.911	***	3.706	***	4.145	***
Up 6 Notches	3.022	***	3.843	***		
Up 8 Notches	3.175	***	4.037	***	4.337	***
LIST_CAR(-7,-1)	**-0.895**	*******	**-0.963**	*******	**-1.235**	*******
LIST_CAR(0,0)	**-1.818**	*******	**-1.512**	*******	**-1.473**	*******
LIST_CAR(1,3)	**0.193**		**0.322**		**0.115**	
SPAN			-0.002	***	-0.002	*******
LIST_RATING			-0.022	*	-0.029	**
NEAR_JUNK			**0.242**	******	**0.291**	*******
NEAR_INVESTMENT			**-1.458**	*******	**-1.469**	*******
LIST_CAR(-7,-1)* NEAR_JUNK					**1.855**	******
LIST_CAR(-7,-1)* NEAR_INVESTMENT					**0.494**	
LN(ASSETS)					-0.009	
ROA					-0.217	
DEBT_RATIO					-0.106	
CASH_RATIO					0.124	
Year Dummy	Yes		Yes		Yes	
R-Square	0.11		0.22		0.25	
AIC	1909.38		1835.78		1775.91	
N	598		598		583	
Equality of Coefficients (F-test)	**Difference**		**Difference**		**Difference**	
H_0:LIST_CAR(-7,-1) = LIST_CAR(0,0)	0.923	*	0.549		0.238	

Table 9: Reaction to One-Notch Downgrade based on Initial Bond Quality

This table examines the effect of bond quality on the magnitude of daily abnormal returns (AR) and cumulative abnormal returns (CAR) over various event windows surrounding the listing date. Abnormal returns are computed using the market model (MKT) as described in Section I. Downgraded by one notch samples are decomposed into different subgroups according to their original listing position. Variables are defined same as before. *, **, *** denotes statistically different from zero based on a standard t-test at the 10%, 5% and 1% levels, respectively.

AR	Downgrade-by-One-Notch					
Day	Downgrade from A+ to A		Downgrade from BBB to BBB-		Downgrade from B+ to B	
-7	0.18%		-0.58%	*	-1.00%	
-6	-0.89%	**	-0.74%		-1.23%	
-5	0.23%		-0.67%		-3.21%	**
-4	-0.46%		-0.91%	**	-1.84%	**
-3	-0.68%		-0.64%		-1.38%	
-2	0.00%		-0.28%		2.96%	*
-1	-0.99%		-1.92%	***	-2.30%	***
0	-2.67%	***	-0.28%		-8.69%	***
1	-0.35%		0.26%		-3.17%	***
2	-0.38%		-0.81%	**	2.54%	**
3	-0.85%	*	0.33%		4.54%	***
CAR	**Downgrade-by-One-Notch**					
Day	**Downgrade from A+ to A**		**Downgrade from BBB to BBB-**		**Downgrade from B+ to B**	
(-60, -1)	-2.19%		-8.97%	***	-19.52%	***
(-30, -1)	-3.73%		-7.91%	***	-13.37%	**
(-7,-1)	-2.62%	*	-5.74%	***	-8.00%	***
(0,0)	-2.67%	***	-0.28%		-8.69%	***
(+1,+3)	-1.57%	**	-0.22%		3.91%	
N.	10		23		12	

-19.52% respectively for high rated (from A+ to A), medium rated (from BBB to BBB-), and low rated (from B+ to B) bonds. The pattern persists for the other pre-listing event windows as well, supporting the conclusions of prior research that for a given magnitude of rating change, the impact of rating changes is greater for lower rated bonds. The key difference, however, is that our results demonstrate equity markets are reasonably good at *predicting* the future rating change before the firm is placed on *CreditWatch*, especially for those firms listed with negative potential. The results once again suggest that *CreditWatch* does not reflect the change in the financial positions of listed firms' timely enough.

D. Conclusion

We examine whether rating agencies are sacrificing timeliness by pursuing rating stability by investigating the response of the equity market to the listing and delisting of firms on S&P's *CreditWatch*, a service whose intended purpose is to improve the timeliness of information about changes in credit ratings. Despite its intended purpose, we find that *CreditWatch* is not completely effective at achieving this goal.

We report three empirical results that support our conclusion. First, we find that equity markets experience substantial positive (negative) abnormal returns for companies listed with positive (negative) potential on *CreditWatch prior* to the listing date. The pre-listing abnormal returns not only reflect the direction, but also the magnitude of rating changes on the delisting date. Second, equity markets exhibit little reaction to the delisting of a company from *CreditWatch*, even when the delisting is accompanied by a change in rating. Third, we find that the pre-listing abnormal returns in equity markets are good predictors of both the direction and the magnitude of the eventual change in credit. This is especially true for those firms listed with negative potential, which is by far the most common listing type. Collectively, our findings suggest that rating agencies may sacrifice timeliness for the sake of stability and that even CreditWatch, which is designed to mitigate the disadvantage caused by rating stability, is not a completely effective instrument.

If an advance notice service such as CreditWatch is already substantially anticipated by the market and too slow in conveying information, credit rating agencies may need to reconsider whether a policy of issuing stable ratings is too costly. In order to repair the reputational damage suffered during the 2007-2008 financial crisis, credit rating agencies must develop more effective measures to convey changes in default probability to the market in a timely manner.

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Appendix I: Credit Rating Transformation

The following is the scale used to transform credit ratings from letters to numerical values, which is consistent with Morgan (2002). Note that the bonds with the highest (lowest) quality receive the lowest (highest) numerical score.

S&P's Credit Rating	Numerical Rating
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC	20
C	21
D	22

Appendix II: Industry Classification

This table summarizes the breakdown of industries represented in the sample by the first digit of the SIC code in Compustat.

1st Digit SIC Code	Positive Potential	Negative Potential	Total	Percent of Total
0	0	2	2	0.34%
1	6	31	37	6.34
2	7	85	102	17.47
3	25	102	127	21.75
4	21	114	134	22.95
5	9	40	49	8.39
6	11	54	65	11.13
7	6	36	42	7.19
8	1	22	23	3.94
9	1	1	2	0.34
Total	97	487	584	

Conclusion

My dissertation focuses on the topic of bank opacity, corporate governance, and credit ratings. In the first paper, I use disagreements on dual-rated debt issues by firms to proxy for information uncertainty and validate Morgan's (2002) finding that rating splits are more likely, and the magnitude of rating gaps are larger, for banks relative to nonbanks. Asset composition and capital are inherent sources of information uncertainty for banks. Opacity is more severe for banks with higher loan and trading asset holdings and lower risk-weighted capital. Importantly, evidence indicates that participation by banks in mortgage-backed asset securitization increases its complexity and opacity. Additionally, I also discover that rating disagreements reflect market proxies of information uncertainty. Last but not least, markets price information uncertainty.

The second paper emphasizes on the potential prevention of systematic risk. The results suggest that systemic risk is caused by excessive investment in opaque assets. Further, evidences indicate that the over-investments in opaque assets are driven by weak corporate governance in compensation mechanism, ownership structure, and board effectiveness in the BHC. Therefore, it turns out that fragile corporate governance leads to excessive investment in opaque assets, which in turn leads to systemic risk.

The third paper investigates the timeliness and stability of default risk announcements made by rating agencies. In particular, I examine whether credit rating agencies, as default risk information producers, are effective in balancing two conflicting demands from the financial market: to maintain rating stability and to convey timely information to the market. Evidences suggest that rating agencies are too slow in making the announcement of credit watch.