Revolving doors on Wall Street

Jess Cornaggia, Kimberly J. Cornaggia, and Han Xia*

February 18, 2013

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*Jess Cornaggia (jesscorn@indiana.edu) and Kimberly J. Cornaggia (kcornagg@indiana.edu) are at the Kelley School of Business at Indiana University and Han Xia (Han.Xia@utdallas.edu) is at the University of Texas at Dallas. The authors are grateful to Lamont Black, Audra Boone, Heski Bar-Isaac, Matt Billet, Peter Cziraki, John Griffin, John Hund, Dirk Jenter, Dave Mauer, Chris Malloy, Shawn O'Donoghue, Joel Shapiro, Denis Sosyura, and Tim Simin for helpful comments as well as audience members at Indiana University and the University of North Carolina Junior Faculty Research Roundtable. The authors thank Sumit Behl for research assistance. Any errors belong to the authors.

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Credit analysts often leave rating agencies to work at firms they rate. Because ratings from other agencies provide counterfactuals, these analyst transfers provide a unique lab for studying revolving door effects. Because rating agencies serve a quasi-regulatory role in capital allocation, abnormal ratings provide a measure of economic consequence of these effects. Using a difference-in-difference approach, we find the transitioning analysts become more favorable to their future employers relative to other raters in the year prior to their transition. Using a KMV model as an alternative benchmark, we find the ratings produced by transitioning analysts become less informative over this period. The timing of analyst transitions relative to new debt issues and watch list appearances does not indicate that firms hire their rating analysts to mitigate information asymmetries. Rather, the evidence suggests that analysts are hired to help issuers and underwriters manage the rating process.

1. Introduction

> When we'd become friendly with an office that was important to us and the Chief of Staff was a competent person, I would say (or my staff would say) to him or her …*'You know, when you're done working on The Hill, we'd very much like you to consider coming to work for us.'* Now the moment I said that … that was it. We owned them… Everything we want, they're going to do… and they're going to think of things we can't think of!
>
> - Jack Abramoff [1]

The conviction of Jack Abramoff in 2006 heightened media attention and sparked academic interest in the revolving door between Capitol Hill and K Street lobbyists, law firms, and corporations.[2] We consider here the potential for a similar influence of investment banks and other securities issuers recruiting their credit rating analysts from the Nationally Recognized Statistical Ratings Organizations (NRSROs) who effectively serve as gatekeepers to capital markets.[3]

On October 22, 2010, a Moody's analyst responsible for rating Royal Bank of Canada (RBC) left Moody's to work for RBC Capital Markets. This transition occurred six months after RBC received Moody's highest rating (Aaa) on a $1 billion debt issue; a rating three notches higher than the rating assigned by Standard & Poor's (S&P). On November 12, 2010, a Fitch analyst covering Wachovia transitioned to Wachovia after upgrading a Wachovia debt issue two notches from A+ to AA, an upgrade not followed by Moody's or S&P.

Such transitions from rating agencies to rated firms have drawn attention from regulators, legislators, and journalists. The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 ("Dodd-Frank", hereafter) recognizes this conflict of interest and requires rating agencies to submit employment transition reports (ETRs) to the U.S. Securities and Exchange Commission (SEC) whenever analysts leave to work for issuing firms they helped rate ("covered

[1] Quote taken from an interview with CBS News on November 6, 2011. For details regarding K Street's influence on public policy, see Abramoff (2011).

[2] We review this literature briefly in Section 2.

[3] See Cantor and Packer (1997), Faulkender and Petersen (2006), White (2010), and Ellul, et al. (2011) for discussion and evidence of the role the NRSROs play in capital markets.

companies", hereafter). We compile these reports to test whether the anecdotal evidence suggesting bias is pervasive among transitioning credit analysts.[4] Each ETR reveals the credit rating agency (CRA) for which the analyst worked, the date she separated from the rating agency, and the identity of the covered company that hired her. If the anticipated employment transition influences ratings, we should observe abnormally favorable ratings in the period prior to when the analysts switch jobs.

These analyst transfers provide a useful lab for studying revolving door effects. Although anecdotes abound, large, verified samples of employee transitions from agencies to industry are rare. Our sample includes 114 transitions, which lend power to the tests. Second, because credit ratings are linked to firms' cost of capital, we can estimate economic effects. Third, the credit ratings industry provides natural counterfactuals: the benchmark analysts' ratings. Fourth, this comparison is less subject to the 'matching' problem that potentially overestimates results in the lobbying and campaign contribution literature. (People who lobby/donate to Republicans are fundamentally different from people who lobby/donate to Democrats.) The credit rating industry mitigates this overestimation concern as the Big 3 raters are more similar in their objectives. Finally, we can further mitigate concerns over biased benchmarks with an alternative, market-based measure of ratings informativeness (a KMV model).

We first identify this potential revolving door effect by comparing through event time the ratings produced by transitioning analysts to benchmark analysts at other CRAs that do not transition to the issuing firm. Our baseline approach is a difference-in-difference analysis: we test whether the ratings produced by transitioning analysts become more issuer-friendly in the period prior to these analysts' transitions relative to ratings produced by the benchmark analysts.[5]

[4] Ljungqvist, et al. (2006, 2007) review the literature examining career concerns and performance determinants among equity analysts. We believe that ours is the first study to examine these themes among credit analysts.

[5] If the transitioning analyst was already more favorable to the issuer, then this effect would exacerbate the difference between raters. However, if the analyst is hired from the CRA with the harsher ratings, then this effect would diminish the difference between raters.

We find that issuers hire rating analysts from the (ex ante) harsher CRA, but that this difference between raters diminishes prior to analyst transitions. Specifically, the difference between the ratings awarded by transitioning and benchmark analysts changes by an average of 0.21 notches (39% of the average disagreement between raters) during the last five quarters leading up to a transition.[6] This result indicates that transitioning analysts award more favorable ratings prior to switching jobs. This result is significant at 1% controlling for issue, year, and rating agency fixed effects. We support this analysis with an alternative benchmark of rating accuracy (a KMV model) and multiple falsification tests.

In our first falsification test, we employ a redacted set of Moody's analyst transitions where analysts took jobs at firms they did *not* help rate.[7] We repeat our baseline difference-in-difference regressions using this redacted sample and we observe no ratings inflation prior to these analysts' separation dates. This result enables us to exclude the alternative explanation for our baseline results that an unobservable coincidental event triggers both the higher credit ratings and the analysts' transfers. If hiring only reflects improved circumstances of the issuer (worthy of higher credit ratings) we should observe the coincidence in the redacted sample of analysts as well as the sample with the conflict of interest. We do not.

Our second set of falsification tests are based on a control group of issuers that do not hire analysts from the Big 3 CRAs in our sample period. We examine these issuers' ratings around hypothetical analyst separation dates. We repeat our baseline regressions and observe no ratings inflation around these hypothetical separation dates. Combined, these non-results corroborate the notion of a revolving door effect: observed ratings inflation is isolated among transitioning analysts in periods prior to their transitions.

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[6] The magnitude of this effect is comparable to the 0.19 notch competitive effect on ratings documented by Becker and Milbourn (2011).

[7] Moody's initially interpreted the Dodd-Frank mandate to require disclosure of all transitions of Moody's analysts to rated firms, irrespective of whether the analyst participated in the rating of her future employer within the prior five years. After conversing with the SEC, Moody's revised its ETRs to only include conflicted analyst transitions; see WSJ (2011.) By compiling Moody's ETRs before and after this update, we were able to isolate a sample of 46 analyst transitions where the analysts did not help rate the firms from which they accepted jobs.

We consider next that the difference between the transitioning analyst and her benchmark may reflect her superior analytical skill, rather than a bias favoring her future employer. To test this hypothesis, we employ a KMV model as an alternative measure of the information content. We find that the correlation between transitioning analysts' credit ratings and the market-based measure of default risk is lowest in the period before the analysts switch jobs. This result corroborates our interpretation of a revolving door effect: transitioning analysts produce ratings that are more favorable and less informative in the period preceding their transition.

Our results reveal the presence of previously untested forces that affect the information production by credit rating analysts. The results are important given the substantial role of credit ratings in the economy and the current legislative effort to reform this industry.[8] We cannot determine whether issuing firms lure otherwise honest analysts (as Abramoff lured congressional staffers) or whether analysts first inflate ratings to seek favor among higher paying employers. Whether the period prior to transition is one of recruitment or audition, our results suggest that the analyst is no longer unbiased in her assessment of her future employer's credit quality.

As a secondary contribution, we explore the potential motivation of the firms hiring these rating analysts. We find only weak evidence that issuers capitalize on inflated ratings by issuing new securities. The number of new bonds issued by covered companies forms a humped shape peaking in the period marked by inflated and uninformative ratings. However, the average issue size decreases steadily over this time period – a result likely attributable to the financial crisis that precedes our analysis. In addition to the timing of bond issues, we analyze proxies for issuer opacity and watch list additions but find no evidence that rating analysts are hired to improve communication with the ratings agency in order to reduce information asymmetry.

The overwhelming majority of analysts transfer to the financial sector, suggesting a natural transfer of talent towards its highest valued use. However, most of our empirical results

[8] The U.S. SEC's Office of Credit Ratings opened on June 18, 2012. More information about this new department is available here: http://www.sec.gov/about/offices/ocr.shtml

are neither predicted nor explained by a benign talent transfer. Overall, the evidence appears most supportive of a gaming hypothesis predicting that issuers and underwriters are better able to understand and manage the rating process after hiring a rating analyst (analogous to hiring an IRS agent to prepare one's income taxes). We find that credit analysts are recruited from the harsher CRA during periods of CRA disagreement. We compare banks hiring rating analysts to other (non-hiring) banks and find that the hiring banks maintain more stable credit ratings following the analysts' transition even though they face higher and more volatile Expected Default Frequencies (EDFs). We find that issuers hiring rating analysts appear especially sensitive to ratings processes. For example, we note that 40% of covered companies are depository institutions, with deposit insurance premiums determined in part by credit ratings; FDIC (2006). We also find that covered companies have significantly greater market share underwriting derivatives and CDOs than a control sample of underwriters in each year from 2000-2007.[9] Whatever the benefit to the hiring financial institutions – talent, ratings management, or both – our primary results indicate that the transitioning analyst is not an unbiased observer. These results suggest a benefit to a "cooling off" period between employment at an NRSRO and a covered company, similar to the three-year rule imposed on auditors by the NYSE and NASD.

2. Literature Review and Hypothesis Development

2.1 Revolving Doors

Existing literature examining the economic effects of revolving doors reports mixed evidence. An early paper by Helland and Sykuta (2001) examines the participation of political directors on boards of regulated firms and concludes that such appointees serve a rent-seeking role. Similarly, Blanes i Vidal, Draca, and Fons-Rosen (2010) document the effects on lobbyist

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[9] Counterparty risk in derivatives markets is assessed in part by bank credit ratings. Buyers require better terms, including increased collateral, from banks without the Aaa rating (Eavis, 2012). We consider CDO market exposure as a proxy for issuer incentive and ability to manage the ratings processes because CDO ratings are highly subjective (see Griffin and Tang, 2012) and more likely inflated than ratings of other securities (see Cornaggia, et al. 2013).

revenues of employing ex-government staffers and conclude that lobbyists sell political access. Luechinger and Moser (2012) document positive abnormal returns around firms' announcements of political appointments from the private sector and corporate appointments of former government officials. A host of accounting papers considers the revolving door between corporations and their auditors, drawing mixed conclusions; see Menon and Williams (2004), Geiger and North (2006), Geiger, et al. (2007), and Naiker and Sharma (2009).

Most recently, DeHaan, et al. (2012) examine the revolving door from the SEC to the private law firms that defend the targets of SEC investigation. In contrast to rewarding favor (leniency) these authors find that the private sector law firms reward the harsher SEC lawyers for their skills. Our approach differs in multiple ways including the research design (difference – in – difference around a specific transfer date). Our design and results could be more cleanly compared to an examination of SEC employees transferring directly to the target firms where the conflict would be acute. Still, because the majority of transfers in our sample are to the financial industry, our results suggest a natural transfer of talent similar to the SEC lawyers to law firms (rather than consulting firms). A comparable study of SEC (or CFTC) employees to litigation consulting firms could shed additional light.

An expanding parallel literature considers the conflict of interest inherent to the issuer-pays rating model and its consequences for rating accuracy; i.e., Mathis, et al. (2009), Sangiorgi, et al. (2009), Kraft (2010), Bolton, et al. (2012), Bruno, et al. (2012), Jiang, et al. (2012), Opp, et al. (2012), Strobl and Xia (2012), Xia (2012), and Cornaggia and Cornaggia (2013). Legislators and popular press suggest that the conflict of interest is egregious in cases where rating analysts leave the rating agency for higher salaries at the firms they formerly rated.[10]

Our revolving door hypothesis pertains only to the incentives of the transitioning analyst. We assume that analyst bias resulting in uninformative ratings would go against the interests of

[10] Rep. Barney Frank, (D., Mass.) is quoted in the *Wall Street Journal:* "You are rating someone and then you want to go work for them and make much more money—the notion that you would be critical of some entity and then hope they hire you goes against what we know about human nature" (WSJ 2011).

the rating agency's reputation. This hypothesis predicts inflated ratings by credit analysts prior to their transition to the issuers they rate. Such rating inflation could manifest in three ways: (1) abnormally high ratings of new debt issues; (2) abnormal upgrades of existing debt; (3) abnormal lack of downgrades of existing debt.

Anecdotal evidence of issuing banks hiring overly-optimistic rating analysts is similar to the large sample evidence of firms hiring optimistic sell-side equity analysts, as documented by Cohen, Frazzini, and Malloy (2012). However, it is important to note that our revolving door hypothesis does not speak to the motives of the hiring firm. Even if the issuing banks (i.e., RBC and Wachovia in our opening examples) recruit analysts to mitigate information asymmetry, the analyst is still conflicted by an anticipated financial interest in the firm she rates.

2.2 Capitalizing on Biased Ratings

After establishing results supporting our primary hypothesis, we explore the myriad of non-competing motivations of the hiring firms. First, we consider that issuers capitalize on their conflicted rating analysts in a manner suggested by the Abramoff example. Issuers benefit from inflated ratings by issuing securities or negotiating other contracts employing credit ratings as benchmarks. Because prevalent institutional rules employ the lower of two ratings (or the middle of three ratings) issuers (or underwriters) benefit most from recruiting the analyst from the harsher of two raters.[11] Moreover, the recruitment period must be sufficiently long to facilitate a lasting benefit of an inflated rating.

Such distortion could not exist in equilibrium if all issuers bribed all analysts at all times. However, we note that a majority of rated firms issue bonds only once.[12] Moreover, we note that

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[11] Regarding institutional rules, see Bongaerts, Cremers, and Goetzmann (2012), NAIC guidelines, or the Basel II accord. For illustration, assume that CRAs rank Fitch, S&P, and Moody's in terms of issuer-favorable ratings for a particular issuer. Between S&P and Fitch, the issuer prefers to inflate S&P. Between Fitch and Moody's, the issuer prefers to inflate Moody's. Less obvious is the preference between inflating S&P or Moody's, depending on ratings volatility and the probability of a "lowest rating binds" rule.

[12] We examine Moody's Default and Recovery Database (DRD) and find 54% of 21,274 corporate issuers (including industrials, transportation, and financial firms) issued debt only one time over the entire Moody's data

CRAs are more concerned with risk assessment at the initial rating than they are with subsequent surveillance; see SEC (2008). Thus, most firms face the cost of capital consequences of credit ratings one time. Only a small fraction of rated firms have frequent repeated interactions with the CRA for the purpose of issuing new securities. Ultimately it is an empirical question as to whether the covered companies hiring credit rating analysts (a) are frequent issuers and (b) capitalize on the inflated ratings.[13]

2.3 Counter-Cyclical Talent Transfer

The model of Bar-Isaac and Shapiro (2011) suggests a non-competing explanation: talent transfers from low paying rating agencies to high paying investment banks. Although a more benign explanation of the hiring firms' motives, this talent transfer is similarly consequential for ratings quality. In this model, ratings accuracy is countercyclical. Rating agencies hire novice analysts and choose the extent to which they invest in the development of these analysts' skills. In economic booms, the probability of skilled analysts being hired away by investment banks is high. The transfer of talented analysts results in a two-fold negative consequence for ratings accuracy. Directly, the CRAs are left with novice analysts. Indirectly, the CRAs invest less in the development of analysts' skills as they expect to lose the talent to the investment banks. (In economic downturns, rating accuracy is conversely predicted to improve.) This talent transfer explanation thus suggests that the impact of the revolving door between CRAs and investment banks is a function of the macro-economy. Testing the cyclicality in ratings quality predicted by this hypothesis requires a lengthy time series of ratings and employee transitions, preferably over several economic cycles, and detailed information regarding the relative aptitude and skill set of the transitioning analysts.

2.4 Asymmetric Information

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history; 55% of banking firms issued only one time over this entire history. For context, Faulkender and Petersen (2006) report that only 19% of public firms issue public bonds.

[13] According to Moody's DRD, 15% of financial institutions issued debt more than twice between 2000-2012. On average, the covered companies hiring rating analysts issue securities every 10 months.

Credit rating agencies exist primarily as information intermediaries, reducing the information asymmetry between issuers and investors. Firms of good type hire CRAs to certify their type in order to obtain lower financing costs than non-certified firms. Of course, firm type is continuous rather than binary. Likewise, the issuer opacity giving rise to the need for the information production is continuous. Both the value and the cost of information production are increasing in the opacity of the issuing firm.[14] Opaque issuers of good type have the greatest incentive to improve their communication with the certifying information intermediary. Hiring credit analysts may serve this purpose. An especially opaque issuer of good type may facilitate the information flow by hiring an analyst from the CRA who can then observe the proprietary information and convey this to his former colleagues in their own credit rating language.[15]

This non-competing explanation suggests that analysts transfer to especially opaque firms. Because investors are sensitive to opacity at the time of a new securities issuance, this motivation for hiring rating analysts would be acute in the period prior to new issues. Likewise, such motivation would arise following the addition of the issuer to the CRA's watch list (another point at which 'good' firms benefit from resolving information asymmetry). Indeed, Moody's (1998) reports an asymmetric Watchlist resolution: 76.44% (65.77%) of issues placed on an Upgrade (Downgrade) Watchlist are upgraded (downgraded).

Like the talent transfer hypothesis, this hypothesis has no prediction regarding biased ratings prior to analyst transition. In contrast to the talent transfer hypothesis, this hypothesis predicts improved ratings quality after the credit analyst joins the issuer or underwriter. Because the issuers' motivation is to improve transparency, this hypothesis is consistent with the conclusions drawn by Che (1995) that the revolving door between regulators and the firms they

[14] Skreta and Veldkamp (2009) conclude that opacity affects ratings accuracy in structured markets.

[15] Such a role for credit analysts is especially compelling after Dodd-Frank repealed CRAs' exemption to Regulation Fair Disclosure (Reg. FD). A lack of access to non-public information curtails CRAs' soft information production abilities (Butler and Cornaggia, 2012). Hiring a rating analyst may help bridge this new information gap within Reg. FD requirements.

regulate potentially results in a socially-beneficial relationship. Reducing the costs of information production results in a more accurate assessment of credit quality, subject to CRA budget and personnel constraints.[16]

2.5 Ratings Management

This hypothesis is similar to the asymmetric information hypothesis, except that here the information transfer is from the CRA to the hiring issuer. The issuers' motivation is not to improve its own transparency, but rather to game the rating process. By hiring a CRA insider, the issuer knows better not only how to game the CRA's model but how to better manage the CRA's evaluation of soft information (i.e., the qualitative analysis beyond the quantitative model).[17] The goal is not only to achieve more favorable current ratings, but to better understand and manage potentially critical analysis going forward. As such, this hypothesis predicts that the analyst should be recruited from the harsher of any two CRAs. (This hypothesis is somewhat related to the work of Jin and Lee (2011), who find that Florida restaurant inspectors become more malleable as they form relationships with regulated firms or individuals.)

Issuers are likely most concerned with ratings management when they anticipate a potential downgrade.[18] Thus, this hypothesis predicts that rating analysts are recruited when covered companies face deterioration in credit quality. If the issuer achieves its 'ratings management' objective, the ex post credit rating should become less responsive to deterioration in underlying credit quality, resulting in an upward biased rating following the analyst transition.

Finally, this hypothesis suggests that analysts should transfer primarily to firms that benefit most from understanding ratings processes and are most sensitive to changes in ratings processes. Such firms include depository institutions that are particularly subject to ratings-based

[16] A recent SEC (2008) examination concludes that limited resources – lack of sufficient personnel in particular – appears to impact the timeliness of rating surveillance by the CRAs (page 21).

[17] Credit ratings issued by Moody's (2002), Standard and Poor's (2003), and Fitch Ratings Inc. (2007), collectively referred to as "The Big 3" raters, are largely qualitative in nature.

[18] Firms are less concerned with upgrades because they convey positive information directly to the market via press release; Ederington and Goh (1998).

regulations; see He, Qian, Strahan (2012). Other candidates are financial institutions heavily involved in the structured financial products markets. An SEC (2008, page 14) examination documents the common CRA practice of over-riding model outputs regarding loss expectations of structured finance products. The value in understanding (and potentially influencing) these out-of-model adjustments increases in issuers' structured finance market share; see He, et al. (2012). Griffin and Tang (2012) report that for CDOs in particular, this subjective ratings process typically favors CDO issuers resulting in AAA tranche sizes 12.1% larger than implied by the CRA model.

2.6 Testing the Hypotheses

For each covered company (hiring a credit rating analyst), we first compare the rating given by the CRA employing the transitioning analyst to a benchmark CRA over event time. We employ Moody's (S&P) as the benchmark agency for transitioning S&P and Fitch (Moody's) analysts. However, because credit ratings definitions and policies differ across agencies, disagreement does not necessarily imply inflation.[19] Thus, we identify ratings inflation as a difference (in event time) in difference (between rating agencies). We perform falsification tests using hypothetical transition dates to issuers that did not hire credit rating analyst in our sample period and, separately, the redacted sample of non-transitioning analysts. We repeat the analysis using a market-based benchmark of rating quality. Specifically, we examine the difference (in event time) in the correlation between the transitioning analysts' ratings and the EDF estimated using a KMV model (detailed in Appendix B). We design these tests to evaluate our primary revolving doors hypothesis pertaining to credit analysts' incentives.

We perform a series of additional tests in order to test the predictions of the secondary hypotheses pertaining to the motivation of the covered companies. We examine whether the

[19] S&P's ratings are intended to reflect relative differences in default probability (S&P, 2011) and Moody's ratings are intended to reflect expected losses (Moody's, 2002). Moody's ratings may be less sensitive to macroeconomic stressors as they explicitly intend to 'rate through the cycle' (Moody's, 2002).

rating analyst is recruited from the (ex ante) harsher CRA. We examine the industrial composition of the covered companies along with proxies of their opacity.[20] We examine the timing of the analyst transfer with respect to new debt issues, watch list provisions, and changes in the covered companies' credit risk (as given by the KMV model). We examine the ratings volatility in event time. We examine the information content of ratings following the analyst departure. And, finally, we consider covered companies' status as depository institutions, their market share in derivatives trading, and their exposure to CDO markets as proxies for their relative sensitivity to the rating process.

3. Sample Selection and Data Collection

3.1 Employee Transitions

Section 15E(h)(5) of the Securities Exchange Act of 1934, as amended by Dodd-Frank, requires NRSROs to report to the SEC cases (retroactively to 2005 and ongoing) where former employees obtain employment with a covered company that was rated within the 12-month period prior to her subsequent employment with the covered company if she:

(i) was a senior officer of the NRSRO;
(ii) participated in determining credit ratings for the covered company;
(iii) supervised an employee that participated in determining the credit ratings.[21]

We compile these employment transition reports (ETRs) in January 2012 from the Big 3 CRAs to form our sample of covered companies. We obtain data for 114 transitioning credit rating analysts and hypothesize a bias regarding the ratings of their future employers. Although not part of our primary sample, we employ the redacted sample of 46 Moody's analysts that were not

[20] Issuer opacity is a necessary condition of the asymmetric information hypothesis which predicts that issuers of good type have an incentive to mitigate opacity.

[21] The statute became self-executing when Dodd Frank became law on July 17, 2010. Current ETR data are available from the SEC. Section 932 of Dodd Frank also requires a "Look-Back Review" of former NRSRO employees who were subsequently employed – within one year – by an entity subject to ratings determined in part by the transitioning employee. If the NRSRO determines that conflicts of interest influenced the rating, the NRSRO is required to place the rating on a watch list and explain the conflict. Unfortunately, results of these reviews are not publicly disclosed. See http://www.sec.gov/news/press/2011/2011-113.htm

responsible for rating their future employer in additional tests. Figure 1 plots the total reported employee transitions by the Big 3 rating agencies through 2011.

[Insert Figure 1 here.]

We have no evidence of non-compliance, but the completeness of the disclosure varies by rater – apparently due to differing initial interpretations of the statute and differing pre-Dodd-Frank internal controls. For example, although the statue requires disclosure of transfers back to 2005, neither Moody's nor S&P disclose any employee transitions prior to 2010. It is possible that there were no employee transitions from Moody's and S&P between July 2005 and July 2010. It seems more likely that these raters' internal controls did not track employee transitions as early as Fitch (which reports transitions back to January of 2006.)

An additional source of difference in disclosure completeness stems from differences in NRSRO interpretation of the statute. Moody's initially disclosed the transitions of any analyst to any firm rated by Moody's, irrespective of whether the analyst was involved in the rating process of the covered firm. This interpretation resulted in over-reporting by Moody's that was revised in February and March 2012. Initially, the sample contained far more analyst transitions from Moody's (82 analysts) relative to S&P (25 analysts) and Fitch (40 analysts).[22] The updated list is more balanced, but Moody's analysts remain most heavily recruited (52 analysts). The inadvertent bonus disclosure of Moody's analysts affords us an additional source of comparison.

3.2 Credit Rating Histories

We obtain ratings histories for the Big 3 raters from Mergent Fixed Income Securities Database (FISD). Each of these CRAs issue ratings along a 21-point alphanumeric scale. Moody's scale ranges from most to least creditworthy: Aaa, Aa1, Aa2 Aa3, A1, A2, A3, Baa1, Baa2, Baa3, Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, and C. The scale employed by S&P and Fitch ranges as follows: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+,

[22] According to the WSJ (2011) these numbers reflect 7.5% of 1,088 Moody's analysts, 3.4% of 712 Fitch analysts and 2.1% of 1,109 S&P analysts.

BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC+, CC, C, and D. Credit ratings equal to Baa3 (BBB-) or higher are considered "investment grade" and obligations with ratings equal to Ba1 (BB+) or lower as "speculative grade." Appendix Table A.1 reports the numerical conversion of these ratings employed in our analysis. Our numeric ratings are decreasing in credit quality such that Aaa = AAA = 1. Hence, a higher numeric value indicates higher credit risk.

3.3 Salary Survey Data

Underlying both the talent transfer hypothesis of Bar-Isaac and Shapiro (2011) and the revolving door hypothesis is the assumption that credit rating analysts make more money after their transition. Our data do not contain salaries. Thus, we tabulate unscientific survey data compiled by Glassdoor.com from Moody's and Goldman Sachs as representative firms in Appendix Table A.2. Our transition data do not specify titles or positions the former credit rating analysts take in the banks that hire them. Assuming rational career development on the part of the transitioning analysts, one might rule out job categories at Goldman Sachs with average salaries below the average analyst's compensation at Moody's. Either way, the upside potential at Goldman Sachs appears higher than that expected at Moody's.[23] Anonymous, self-reported survey data are not verifiable, but these estimates reflect the more lucrative career paths assumed by Bar-Isaac and Shapiro and the authors of the Dodd-Frank legislation.

3.4 Underwriters, Analysts, Yields, and Financial Data

We collect CDO underwriting information from the ABS database managed by J.P. Morgan's Asset-Backed Alert. We manually merge our sample of covered companies with the ABS database, by name. We obtain lead underwriters for corporate bond issues and bond yields from Mergent FISD. We obtain analyst coverage from I/B/E/S. We obtain stock price and accounting data from CRSP and Compustat, respectively. Finally, we obtain data on derivatives

[23] These survey data do not contain salary information above Vice President level at Moody's or Goldman Sachs.

underwriting activities from the *Quarterly Report on Bank Trading and Derivatives Activities* from the Comptroller of the Currency Administrator of National Banks.

4. Empirical Results

4.1 Descriptive Statistics

Table 1 reports the transitions of 160 credit rating analysts from Big 3 raters (Moody's, S&P, and Fitch) according to reported separation dates by sample quarter (Panel A) and classifies the covered companies hiring 169 total NRSRO analysts by type (Panel B). Panel A separates Moody's disclosure into transitioning and non- transitioning analysts. Like Figure 1, this panel indicates that of the Big 3, only Fitch disclosed employee transitions prior to the 3rd quarter of 2010.

[Insert Table 1 here.]

Panel B classifies covered companies as Banks or Brokers, Asset Managers, Insurers, or 'Others' including information intermediaries (Morningstar and Thomson Reuters), a Canadian pension plan, multiple energy companies and consulting firms, public issuers, and industrials such as Alpina and Samsung. The complete sample (including the bonus reporting of non-transitioning analysts by Moody's removed from the public disclosure in February and March 2012) indicates an over-representation of financial institutions among the covered companies hiring rating analysts. Several banks hire multiple analysts: Deutsche Bank hires nine (9) analysts between May 2010 and September 2011; Credit Suisse hires seven (7); Barclays and UBS each hire six (6); and Citigroup, Bank of Tokyo, and Morgan Stanley each hire five (5) analysts. The talent transfer hypothesis predicts this clustering of covered companies in the financial sector, assuming the skill set required for credit analysis is more readily employed by banks than industrial firms. To the extent that financial institutions are more opaque than industrials, as argued by Morgan (2002), this clustering is also consistent with the prediction of the asymmetric information hypothesis.

Table 2 Panel A reports summary statistics for rating levels from each CRA. Because numeric ratings are decreasing in credit quality (increasing in credit risk) a smaller number indicates that the rater listed first is more favorable to the issuer. Row (1) employs the sample of bond issues for which Moody's analysts transition to the issuers they rate. Row (2) employs the sample of bond issues for which S&P analysts transition to the issuers they rate. Row (3) employs the sample of bond issues for which Fitch analysts transition to the issuers they rate. We evaluate ratings on quarterly basis in the period from 12 quarters before each analyst's separation date to four quarters after the separation date. The last column reports differences between the mean of ratings from S&P and Moody's, and from Fitch and S&P, respectively. These differences are significant at 1% and we conclude that Fitch's ratings are, on average, most favorable to issuers and Moody's are least favorable.

[Insert Table 2 here.]

This descriptive table does not test any hypothesis. The event time period includes a full year after the separation date and the sample includes observations for which covered companies also hire analysts from benchmark rating agencies (i.e., hires from both Moody's and S&P). Table 2 conveys average differences (before and after the analyst separates) suggesting differences in CRAs more generally. Because CRAs have different ratings philosophies and technologies, we should not expect zero unconditional divergence of opinions. Moreover, our sample of covered companies is dominated by financial institutions (see Table 1) which exhibit greater disagreement in ratings than industrials; see Morgan (2002). In order to examine ratings by transitioning analysts, we exclude covered companies that hire analysts from multiple sample CRAs from later analyses.

The split ratings (disagreement among the CRAs) in our sample appear comparable to the broader sample studied by Bongaerts, et al. (2012). These authors report that Moody's and S&P disagree in 33% of issues rated by both and that the average dispersion between these two raters is 0.42 notches. Our finding that Fitch's ratings are generally most favorable to issuers is also consistent with their evidence.

Panel B of Table 2 provides summary statistics for three simple proxies for the opacity of our covered companies compared to a control group of issuers. The most obvious proxy for information asymmetry is whether a firm is public or private. Similarly, prior researchers conclude that larger firms are more transparent (Vermaelen, 1981; Diamond and Verrecchia, 1991; and Lang and Lundholm, 1996). Finally, Ederington and Goh (1998) find that equity analysts' recommendations Granger cause CRA rating changes, thereby revealing information regarding firms' credit quality. Hence, firms covered by more analysts should be more transparent. Our sample of covered companies has a higher percentage of public firms (significant at 1%). Of the public firms, the covered companies are larger (significant at 1%) and have greater analyst following (significant at 10%). These simple measures are inconsistent with the prediction of the asymmetric information hypothesis that covered companies should be more opaque.

4.2 Non-Transferring Rating Analysts as Benchmarks

In order to ensure a clean benchmark, we discard observations for which the covered company also hired an analyst from the benchmark CRA in analyses starting with Table 3. We report the average rating difference between the agency with a transitioning analyst and its benchmark agency without an identified transitioning analyst in Table 3 column 3. Because raw rating differences are contaminated by calendar year effects, we adjust the rating difference by subtracting the average rating differences in the same calendar year for all rated issues in our sample.[24] Differences are reported by quarter-to-separation starting from eight quarters prior to analysts' separation dates.

[Insert Table 3 here.]

[24] Our results and interpretations are robust to raw rating differences without adjusting for calendar year effects.

Table 3 illustrates the basic evidence of the conflict of interest surrounding analysts' career transition to covered companies. Because numeric ratings are decreasing in indicated credit quality (increasing in indicted credit risk), the significantly positive average difference between transitioning and benchmark analysts observed in Q_{-8} through Q_{-6} indicates that subsequently hired analysts award harsher ratings in this early time period. However, this difference reverses in the period leading up to the analyst separation, starting with Q_{-5}. By Q_{-2}, the CRA with the transitioning analyst awards a significantly more favorable rating compared to the benchmark CRA. By the third quarter following the analyst transition, this originally harsh CRA is again significantly harsher than the benchmark, but less so than in the earliest period prior to the conflict. We plot these differences in Figure 2 in order to demonstrate the basic U-shape.

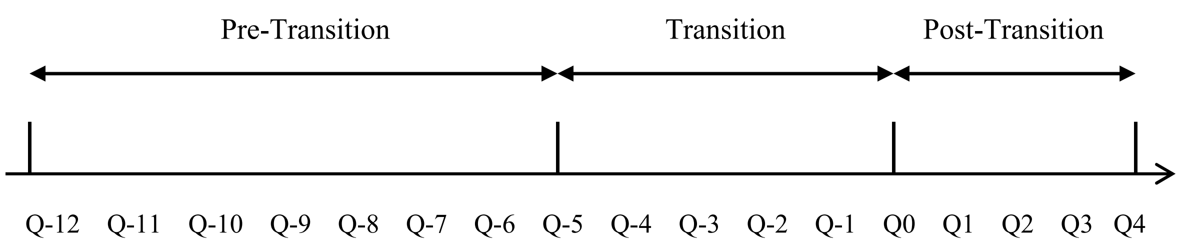
[Insert Figure 2 here.]

These differences in average ratings between CRAs in Table 3 reflect differences in CRA rating philosophy and technology as noted above, as well as any causes or effects of the analysts' transitions. We thus include rating agency fixed effects in regression models to control for these differences. We examine the time trend of rating differences between transitioning and benchmark analysts starting with the following model.

$$\text{Rating Difference}_{i,t} = \alpha + (\beta_{1\text{-}12})\ \text{Quarter}_t + \text{fixed effects} + \varepsilon \qquad (1)$$

The dependent variable in model (1) is the numerical difference in ratings of bond i in quarter t between the transitioning and benchmark analysts. Independent variables are indicators for event time quarter, from eight quarters prior (Q_{-8}) through four quarters following (Q_{+4}) each analyst's separation date. The event quarter when an analyst separated (i.e., Q_0) is omitted as the baseline. Issue Fixed Effects are indicator variables for bond issues. Year Fixed Effects are indicator variables for calendar years. Rating Agency Fixed Effects are indicator variables for analysts departing S&P, Moody's, or Fitch. Standard errors are clustered at the issuer level.[25] Plots of beta coefficients resemble the U-Shape in Figure 2. Coefficients for differences in quarters Q_{-3}, Q_{-2}, and Q_{-1} are significantly negative (at 5%, 5%, and 10%, respectively) suggesting a more issuer-friendly rating by the transitioning analysts, controlling for CRA fixed effects. This result is predicted by the revolving door hypothesis.

We compress the time series in Table 4 regression models and test the differences between the transitioning analysts and benchmark ratings, over three distinct time periods spanning 12 quarters prior to four (4) quarters following the analysts' separation date. Based on results from Figure 2 and Table 3, we identify the five quarters preceding the analyst separation date as the "transition period".[26]



In Table 4, the transition period is compared to the subsequent (post-transition) period in model (2) and compared to the prior (pre-transition) period in model (3). Time period indicators in Table 4 are as follows:

Transition =1 if [-5, 0] and =0 if (0, +4]

Pre-Transition =1 if [-12, -5) and =0 if [-5, 0]

We delete bonds issues whose observations are from only one of the three periods (pre-, post-, or transition), since they don't generate variation in our independent variable in our following issue-

[25] Alternatively, we cluster standard errors at the issue level. We report results throughout based on the more conservative (least significant) standard error clustering at the issuer level. We revisit our baseline models in a robustness section of the paper employing the aggregate issuer-level rating in lieu of issue-level bond ratings.

[26] We obtain qualitatively similar results defining the transition period as six quarters preceding the separation date.

fixed effects analyses. (Including these observations generates nearly identical results.) The dependent variable in both models is the numerical difference (between transitioning and benchmark analysts) in ratings of bond i in quarter t. We employ Issue, Year, and Rating Agency fixed effects in both models in an OLS specification.[27]

$$\text{Rating Difference}_{i,t} = \alpha + \beta_1 \text{ Pre-Transition} + \text{fixed effects} + \varepsilon \qquad (2)$$

$$\text{Rating Difference}_{i,t} = \alpha + \beta_1 \text{ Transition} + \text{fixed effects} + \varepsilon \qquad (3)$$

Because numeric ratings are decreasing in credit quality (increasing in credit risk), the significant coefficients in models (2) and (3) indicate that the relative ratings form a U-Shape. The CRA with the transitioning analyst is more favorable to the covered company in the transition period [-5, 0] compared to either the prior period [-12, -5) or the period following her transition (0, +4]. This result is predicted by the revolving door hypothesis.[28]

[Insert Table 4 here.]

We estimate the potential economic significance of the 0.22 notch difference (in the biased rating relative to its benchmark) between the pre-transition and transition time periods observed in Table 4 model (2) as follows. The bonds in our sample are rated A1, on average. Of the A1 rated bonds issued between 2007 and 2011 (or test period), the average yield is 4.82%. The average yield for Aa3 rated bonds (one notch higher than A1) in this period is 5.46%; a 64 basis point difference between A1 and Aa3. Assuming linearity, an average 0.22-notch increase indicates an average 14 basis-point difference in the cost of capital. The average face value of bonds issued in our test period is $134 million, so this rating inflation amounts to $187,600 for

[27] The ordered logit model is not robust to fixed effects and can accordingly generate biased coefficients and standard errors due to the incidental parameter problem. For this reason, we employ the OLS specification following Becker and Milbourn (2011), Baghai, Servaes, and Tamayo (2012), and Jiang, Stanford, and Xie (2011).

[28] We report the within-issue R squared to capture the explanatory power of our independent variable within each bond issue. Alternatively, we place bond issue indicator variables in the regression and obtain an R squared that takes into account of the indicators. In that case, we obtain a higher R2 (approximately 80%-90%). This is consistent with Becker and Milbourn (2011) since the indicator variables capture over 70% variation of bond issue ratings.

an average bond. In our sample, the average issuer has 156 bonds outstanding (at the parent company level) during 2007 and 2011, suggesting a $29.3 million effect.

In our first falsification test, we consider separately the sample of non-conflicted analyst transfers initially disclosed by Moody's in models in the latter columns of Table 4. Because Moody's is the only rating agency to disclose non-conflicted transfers, we omit CRA fixed effects for these latter specifications. The insignificance of the explanatory variables in the subsample of non-conflicted Moody's analyst transitions indicates the results in models (2) and (3) are unique to the sample with transitioning analysts.

The following additional falsification tests are un-tabulated. We re-employ fixed-effect OLS models (2) and (3) in order to examine changes in rating differences around hypothetical separation dates for a control group of issuers that did not hire ratings analysts at any point during our sample period. Specifically, for each observation of a CRA with a transitioning analyst, we select an alternative issuer rated by this CRA (that did not hire a ratings analyst) and compare its ratings from this CRA to its ratings from the benchmark CRA. We consider hypothetical separation dates in every quarter from 2010 Quarter 1 to 2011 Quarter 4 and cannot replicate the significant results obtained in Table 4. The insignificance of these hypothetical Transition and Pre-Transition time periods indicate that the significant results in Table 4 are unique to transitioning analysts.

4.3 An Alternative (KMV) Benchmark

As an alternative gauge of ratings accuracy, we employ a distance-to-default model based on Merton/KMV as a measure of ratings' information content. We describe in Appendix B a standard estimation procedure for the Expected Default Frequency (EDF). A higher EDF value indicates a higher default probability and lower credit quality for the firm. Since EDF reflects the market's assessment of firms' credit quality, this measure circumvents the potential problem of non-comparable CRA benchmarks employed in our primary results reported in Section 4.2. With this alternative benchmark, we infer that credit ratings are more informative the greater their correlation with the market-based EDF.

Because our sample period (2010-2012) follows the financial crisis, during which EDFs were especially high among financial institutions, we consider both raw and 'idiosyncratic' EDF. We define idiosyncratic EDF as the portion unexplained by the macroeconomic environment. In order to measure this variable, we first regress EDF on indicator variables for calendar years 2008 – 2012 (i.e. year dummies) in an issue-fixed effect setting to predict EDF attributable to macroeconomic conditions. Idiosyncratic EDF is the difference between the observed EDF and that predicted by the time dummy model. Because financial institutions were also downgraded during the crisis, we similarly measure idiosyncratic ratings as those unexplained by the time dummy model. This approach aims to take out the market-wide change in EDFs and ratings driven by the onset and offset of the subprime financial crisis.

We plot in Figure 3 the idiosyncratic EDF and credit rating for our sample of covered companies in event time. The sample consists of quarterly observations of ratings from CRAs with transitioning analysts from 12 quarters prior through four quarters following the analyst separation date. Several observations are worth noting. First, an average covered company experienced highly volatile idiosyncratic EDF in the Pre-Transition period [-12, -5), a period that overlaps the onset of financial crisis.[29] Moreover, idiosyncratic ratings exhibit high co-movement with EDF during this Pre- Transition period.

In the Transition period [-5, 0], the previously volatile EDF gives way to a steadily increasing idiosyncratic EDF.[30] This deterioration in credit quality continues through the Post-Transition period (0, +4].[31] More importantly, the idiosyncratic ratings no longer exhibit the co-

[29] The idiosyncratic EDF for covered companies ranges -0.05 to 0.15 during this Pre-Transition period, during which the raw EDF averages 68%.

[30] Although the idiosyncratic EDF is between -0.10 and 0 in the Transition period, the average raw EDF for these firms is 36% during this time period.

[31] The raw EDF for covered companies averages 17% over this final (Post-Transition) time period. However, it increases significantly to 46% by the end of 2011.

movement observed in the earlier Pre-Transition period. Rather, ratings flatten out during the Transition period and remain unresponsive to these firms' declining credit quality through the Post-Transition period. The revolving door hypothesis predicts unresponsive ratings in the Transition period. Ratings unresponsive to deteriorating credit quality in the Post-Transition period are predicted only by the ratings management hypothesis.

[Insert Figure 3 here.]

We test this interpretation of Figure 3 with a falsification test employing financial institutions that do not hire a credit rating analyst. Because there is no event, Figure 4 plots idiosyncratic EDF and credit rating of this control sample over calendar time quarterly from Year 2007 Quarter 1 through Year 2011 Quarter 4.

[Insert Figure 4 here.]

As observed in Figure 3, the control group in Figure 4 exhibits both high volatility in idiosyncratic EDF and high co-movement in credit ratings during the financial crisis. However, different from that of covered companies in Figure 3, the credit risk of firms in the control group does not experience significant deterioration in credit quality following the crisis. Rather, the relatively flat EDF line indicates that these firms' risk profile remained stable from 2010. However, despite of the relative stability of EDF in the latter half of the time series, credit ratings in the control group remain volatile. Where ratings appear non-responsive to EDF in Figure 3, ratings appear over-responsive to changes in EDF in Figure 4. We thus conclude that the evidence supporting the ratings management hypothesis in Figure 3 is specific to covered companies.

We formally explore these patterns in a multivariate framework next. We start by examining the change in rating responsiveness (informativeness) to covered companies' EDF over event time. Specifically, we employ the following fixed-effect OLS regression model:

$$\text{Rating}_{i,t} = \alpha + \beta_1 \text{ EDF}_{i,t} + (\beta_{2\text{-}13}) \text{ Quarter}_t + (\beta_{14\text{-}25}) \text{ EDF}_{i,t} \times \text{Quarter}_t + \text{fixed effects} + \varepsilon \quad (4)$$

The dependent variable is the numerical value of the transitioning analysts' rating of bond i in quarter t in each quarter beginning eight quarters prior to her transition (Q_{-8}) through four quarters after (Q_{+4}). The event quarter of separation (Q_0) is omitted as the baseline. The first independent variable is the issuer's estimated EDF. The explanatory variables of interest are the interaction terms between the EDF and the event time quarter dummies. The model includes Issue, Year, and Rating Agency fixed effects and standard errors are clustered at the issuer level.

Un-tabulated results reveal that the average rating from the CRA with a transitioning analyst is significantly positively related (at 5%) to the EDF seven quarters prior to separation (Q_{-7}) but is not again significantly related until three quarters following the analyst's transition. The uninformative ratings (unrelated to EDF) observed prior to the analysts' departure are consistent with Figure 3 and are predicted by the revolving door hypothesis.

As in Table 4, we compress the time series in Table 5 regression models. Here, we test the differences in the information content of ratings (based on the EDF benchmark) in same three time periods spanning 12 quarters prior to four (4) quarters following the analysts' separation date. As before, the five quarters preceding the analyst transition date are identified as the Transition period. The Transition period is compared to the subsequent (Post-Transition) period in model (6). The Transition period is compared to the prior (Pre-Transition) period in model (5). Finally, we discard the Transition period and compare the period preceding and following the Transition period in model (7). To summarize, period indicators in Table 5 are:

Pre- Transition =1 if [-12, -5) and =0 if [-5, 0]
Transition =1 if [-5, 0] and =0 if (0, +4]
Post- Transition = 1 if (0, +4] and =0 if [-12, -5)

The dependent variable in these fixed-effects OLS models is the numerical value of the bond ratings from the CRA with a transitioning analyst.

$$\text{Rating}_{i,t} = \alpha + \beta_1 \text{ EDF}_{i,t} + \beta_2 \text{ Pre- Transition} + \beta_3 \text{ EDF}_{i,t} \times \text{Pre- Transition} + \text{fixed effects} + \varepsilon \quad (5)$$

$$\text{Rating}_{i,t} = \alpha + \beta_1 \text{ EDF}_{i,t} + \beta_2 \text{ Transition} + \beta_3 \text{ EDF}_{i,t} \text{ x Transition} + \text{fixed effects} + \varepsilon \quad (6)$$

$$\text{Rating}_{i,t} = \alpha + \beta_1 \text{ EDF}_{i,t} + \beta_2 \text{ Post-Transition} + \beta_3 \text{ EDF}_{i,t} \text{ x Post-Transition} + \text{fixed effects} + \varepsilon \quad (7)$$

Each specification includes Issue, Year, and CRA fixed effects. The results of these models are tabulated in Table 5. Standard errors clustered at the issuer level are in parentheses.

[Insert Table 5 here.]

Because numeric ratings are decreasing in credit quality (increasing in credit risk), the significant coefficients on the interaction terms in models (5) and (6) indicate that information content of the ratings forms a U-Shape. The rating from the transitioning analyst is least informative in the period [-5, 0] compared to either the prior period [-12, -5) or the period following her transition (0, +4]. This pattern is predicted by the revolving door hypothesis.

Given the identified conflict, we discard the [-5, 0] period and compare the Pre-Transition and Post-Transition time periods in model (7) in order to test the contrasting predictions of the asymmetric information and talent transfer hypotheses. The former (latter) predicts that ratings become more (less) informative after the transition. The results indicate that ratings are less informative in the period following the analyst departure, consistent with the predictions of the talent transfer and ratings management hypotheses.

We perform, but do not tabulate, falsification tests similar to those performed for Table 4. Specifically, we revisit models (5) and (6) using a control group of issuers that did not hire rating analysts. Because there is no event, we examine hypothetical separations in every calendar quarter from 2010 Quarter 1 to 2011 Quarter 4. Again, the primary variables of interest are the interaction terms. The insignificant coefficients throughout all specifications generate two implications. First, they suggest that the U-Shape in the information content observed in models (5) and (6) of Table 5 is specific to covered companies, further supporting the revolving door hypothesis. Second, they indicate that ratings informativeness does not change over time for firms in this control group, in contrast to the pattern in model (7) of Table 5. This observation is consistent with Figure 4 and further suggests covered companies' incentive to manage ratings through hire.

4.4 The Timing of Analyst Transitions

Figure 3 suggests one motivation for the timing of the analyst transitions to our sample firms: covered companies appear to be managing credit ratings in the face of deteriorating credit quality. We explore additional potential explanations for the timing of the analyst transitions to further differentiate between the hypotheses pertaining to the covered companies. In particular, we consider whether covered companies hire away rating analysts to mitigate information asymmetries around a new debt issuance, in which case the transfer should precede the issue. In contrast, if covered companies capitalize on the inflated ratings, we should observe analyst transfers after new debt issues. This is particularly important given the reversal of the inflating ratings observed after the analysts' departure from the CRA.

Summary statistics in Table 6 indicate that covered companies issue more new bonds in the Transition period [-5,0] and fewer bonds in the subsequent period (0, +4]. This observed pattern is less supportive of the asymmetric information hypothesis than capitalizing on inflated ratings. During the Transition period, the mean issue amount is $77,657,000 and significantly larger (at 1%) than average $45,961,000 issued in the Post-Transition period. However, this result may reflect a general time trend following financial crisis. Indeed, the average amount ($168,769,000) issued in the Pre-Transition period is significantly larger than either Transition or Post-Transition. The average dollar amount issued is decreasing over our time period. Only the number of issues is hump-shaped as predicted by the capitalizing on inflated ratings hypothesis. As such, we cannot conclude that new debt issues explain the timing of the analyst transitions.[32]

[32] We note that much of the analyses pertaining to the motivation of the hiring firms would benefit from a longer time series less sensitive to the financial crisis. However, we believe we provide ample compelling evidence in support of our primary revolving door hypothesis and sufficient suggestive evidence to warrant consideration of the secondary hypotheses.

[Insert Table 6 here.]

We also consider whether covered companies hire away rating analysts to help combat potential downgrades resulting from potentially inefficient information communication between the two parties. Specifically, we explore the incidence of covered companies placed on credit watch lists relative to the analyst transition dates. The premise of the asymmetric information hypothesis is that hiring credit analysts mitigates information asymmetry between the issuer and the rating agency. A new addition to a CRA watch list is an important point to mitigate information asymmetry. But in order to support the asymmetric information hypothesis, the analyst transferred should (a) come from the credit rating agency placing the covered company on a watch list and (b) follow shortly after the watch list announcement. We find no such evidence. Summary statistics indicate that, on average, the last time covered companies hiring S&P analysts were on S&P's watch list was more than five years before the separation date. For Moody's and Fitch, the average time between the last watch list and the later analyst separation is three years. Table 7 reports summary statistics for watch list appearances of covered companies hiring rating analysts compared to a control group.

[Insert Table 7 here.]

Finally, we consider that if the rating agencies viewed the departure of these analysts as problematic, they might place the covered companies on watch lists after the separation date. We find no such evidence that they do so. This lack of official publicly-announced review does not preclude an internal audit. However, the apparent lack of internal controls tracking the transitions of analysts to covered companies (Figure 1 and Table 2) suggests the rating agencies do not view this as a cause for concern.

4.5 Sensitivity to Ratings Methodologies

Combined, Figures 3 and 4, along with the formal tests in Table 5, support the ratings management hypothesis. Covered companies hiring rating analysts face a sharp deterioration in their EDFs both preceding and following analysts transfer, which is not observed in a control sample of financial institutions. However, ratings for covered companies are less responsive to changes in EDF than ratings of the control group. Evidence that covered companies hire away the harsher analyst (Table 3) is also predicted by the ratings management hypothesis.

We consider here the sensitivity of the covered companies to the credit ratings process to further explore this hypothesis. Because the FDIC (2006) relies on credit ratings to differentiate risk and establish depository insurance premiums, we consider the representation of depository institutions in our sample of covered companies. Panel A of Table 8 indicates that 40% of our covered companies (or their parents or their subsidiaries) are depository institutions. This percentage is significantly greater (at 1%) than the 25% of 670 financial institutions (NAICS 52xx) that issue rated bonds but do not hire rating analysts. Because bank credit ratings affect derivatives business (Eavis, 2012) we consider also the representation of derivatives underwriters in our sample of covered companies hiring rating analysts. The *Quarterly Report on Bank Trading and Derivatives Activities* (obtained from the Comptroller of the Currency Administrator of National Banks) reports the derivatives underwriting by the top 25 individual underwriters and for the balance of the industry on a quarterly basis. We aggregate these data to an annual level and report the percentage of our sample of covered companies identifies in the top 25 underwriters in Panel B of Table 8. Our sample firms account for 27.6% to 52% of the top derivatives underwriters over the 2000-2011 period. By comparison, the control group of 670 financial institutions that issue bonds but do not hire rating analysts account for 4.3% to 6.11% over this time period.

[Insert Table 8 here.]

Under the ratings management hypothesis, the issuers' motivation is not only to understand but to game the rating process. By hiring a CRA insider, the issuer knows better how to manage the CRA's evaluation of soft information (i.e., the qualitative analysis beyond the quantitative model). Griffin and Tang (2012) document the subjectivity of credit ratings of CDOs, in particular. We compare the CDO underwriting activities of our covered companies to a control sample of underwriters in Panel C of Table 8. We are not testing the CDO ratings directly. Rather, we employ the exposure to the CDO market as a proxy for the benefits of ratings management.

CDO underwriting activity is tabulated in millions of dollars and as a percentage market share, in each year from 2000 through 2007 and in two four-year time periods (2000-2003 and 2004-2007). The differences between these groups are significant at 1% in each year and in both time periods.[33] To the extent that the CDO underwriting activity provides a reliable proxy for these issuers' sensitivity to the ratings process, these results provide additional support for the ratings management hypothesis.

4.6 Robustness Checks

Our baseline results reported in Tables 4 and 5 employ the full sample of bonds issued by covered companies hiring rating analysts. These regressions employ issue-level fixed effects and cluster standard errors at the issuer level. To ensure that our results are not an artifact of over-sampling, we revisit these baseline results employing a restricted sample of credit ratings aggregated to the issuer-transition level. Because an individual covered company may hire multiple rating analysts at different times, we aggregate the ratings data to each issuer-transition pair. For covered companies with multiple bonds outstanding, we employ the median bond rating in event time.[34] Regressions in Table 9 employ this restricted sample, employing more stringent issuer-transition fixed effects in lieu of issuer fixed effects employed in Tables 4 and 5. As such, these results purely capture the time variation of ratings within each issuer-transition pairing.

[33] The increase in CDO underwriting activity observed in Table 8 is consistent with the evidence provided by Shivdasani and Wang (2011) and Nadauld and Weisbach (2012).

[34] Employing the mean bond rating generates similar results.

These models do not employ the credit rating agency fixed effects as there is no variation in CRAs within each issuer-transition pair.

[Insert Table 9 here.]

Overall, the baseline results reported in Tables 4 and 5 are robust to the restricted sample of issuer-level ratings. Model 2 and Model 3 in Panel A of Table 9 demonstrate the same basic U-Shape in rating differences observed in Table 4. Like Table 5, Panel B of Table 9 indicates that the ratings from CRAs with transitioning analysts are significantly more informative in the Pre-Transition period, compared to the Transition period (Model 5). Likewise, the ratings from these CRAs are significantly less informative in the Post-Transition period than they were in the Pre-Transition period (Model 7). Only Model 6 loses significance, suggesting that the Transition period is indistinguishable from the Post-Transition period. This result is consistent with the ratings management hypothesis. Indeed, in unreported plot, we confirm that the patterns for issuers' idiosyncratic EDF and credit ratings closely resemble those in Figure 3. Taken together, these results suggest our previous findings do not reflect an artifact of over-sampling.

5. Conclusion

The transition of credit analysts from rating agencies to the firms they rate has become a public policy concern. Legislators and popular financial press suggest a conflict of interest: the promise of lucrative investment banking jobs in particular inhibits critical examination of the banks themselves and the issues they underwrite. We find evidence to support this conjecture. We employ a difference (in event time) in difference (between transitioning and non-transitioning rating analysts) approach and find that ratings from agencies with transitioning analysts are inflated in the period preceding their transition to the issuer. Similarly, the transitioning analysts' ratings appear less informative based on a KMV model in this period.

Overall, we conclude that revolving door effects influence credit ratings. Although issuers appear to capitalize on the ratings inflation by issuing more new securities in the period marked by inflated ratings, these new issues appear to be in smaller than average amounts. We find no evidence that rating analysts are hired to improve communication with the ratings agency in order to increase the transparency of the issuer. Rather, it appears that analysts are hired to help manage the rating process.

Appendix A

Hypothesis pertaining to transitioning credit rating analysts:

Hypothesis	Rating Bias	Rating Accuracy / Informativeness
Revolving Door	Inflated ratings of issuing firms in the period prior to analyst transitions	Ratings are less informative in the period prior to analyst transitions

Hypotheses pertaining to the covered companies:

Hypothesis	Timing of Transfer	Analyst hired from harsh or lenient CRA	Classification of Issuers Hiring Credit Rating Analysts	Rating Accuracy / Informativeness
Capitalizing on inflated ratings	Transfer should follow a debt issue with inflated rating	Recruit the harshest analyst	No prediction	Less informative prior to analyst transitions
Talent transfer	Transfer volume should correlate with cycles (more in booms)	No prediction	Analysts transfer to finance industry	Less informative after analyst transitions
Asymmetric information	Transfer should precede a debt issue or follow watch list addition	No prediction	Concentration in issuers with more information asymmetry	More informative after analyst transitions
Ratings management	Transfer should follow deterioration in issuer's credit quality. This deterioration is likely to continue following transfer	Recruit the harshest analyst	Concentration in issuers most sensitive to changes in rating process	Ratings become less responsive to deterioration in credit quality after transitions (less informative with bias)

Appendix B

KMV Methodology

We employ a market-based measure of default risk estimated by Drucker and Puri (2009) which is, in turn, based on KMV/Merton methodology described in Crosbie and Bohn (2003).

$$Default\ risk = \frac{V_A - D}{V_A * \sigma_A},$$

where D is the amount of debt, defined as the debt in current liabilities plus one-half long-term debt. V_A is the market value of assets and σ_A is the one-year asset volatility. V_A and σ_A are unobservable, but are approximated by using the market value of equity (V_E), the past-one-year equity volatility (σ_E), the three-month treasury bill rate (r), and debt (D) and by solving Merton's (1974) model of pricing a firm's debt and equity for a one-year time horizon (T=1):

$$V_E = V_A * N(d_1) - e^{-rT} * D * N(d_2) ,$$

$$\sigma_E = \frac{V_A}{V_E} * N(d_1) * \sigma_A ,$$

where

$$d_1 = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}},$$

$$d_2 = d_1 - \sigma_A\sqrt{T},$$

and N(.) is the cumulative normal distribution.

The Expected Default Frequency (EDF) is then calculated as $N(-d_3)$, where

$$d_3 = \frac{\ln\left(\frac{V_A}{D}\right) + \left(\mu - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}},$$

and μ is the annualized asset return, calculated using the estimated asset value V_A.

Table A.1 – Numerical Credit Ratings

This table displays numeric conversions of Moody's, Fitch, and S&P alphanumeric credit ratings scales. Credit ratings less than 11 are investment grade, credit ratings greater than 10 are speculative grade. Our numeric ratings are decreasing in credit quality such that Aaa = AAA = 1. Hence, a higher numeric value indicates higher credit risk.

Investment grade			Speculative grade		
Moody's scale	S&P and Fitch scale	Numeric rating	Moody's scale	S&P and Fitch scale	Numeric rating
Aaa	AAA	1	Ba1	BB+	11
Aa1	AA+	2	Ba2	BB	12
Aa2	AA	3	Ba3	BB-	13
Aa3	AA-	4	B1	B+	14
A1	A+	5	B2	B	15
A2	A	6	B3	B-	16
A3	A-	7	Caa1	CCC+	17
Baa1	BBB+	8	Caa2	CCC	18
Baa2	BBB	9	Caa3	CCC-	19
Baa3	BBB-	10	Ca	CC	20
			C	C	21
				D	22

Table A.2 – Salary survey data

This table reports average, minimum, and maximum salaries by job title at Moody's Investors Service and Goldman Sachs. These data are anonymously self-reported through Glassdoor.com. There are no data available on positions above the Vice President in either organization.

Employer	Position	# Employees reporting	Average salary including bonus	Lowest reported salary	Highest reported salary
Moody's	Financial data analyst	9	$51,931	$40,000	$75,000
	Financial analyst	9	$83,063	$50,000	$140,000
	Associate analyst	54	$104,073	$60,000	$130,000
	Analyst	22	$149,292	$100,000	$200,000
	Assistant Vice President	20	$156,147	$93,000	$200,000
	Vice President	16	$235,422	$128,000	$409,000
Goldman Sachs	Analyst / developer	315	$91,735	$60,000	$131,000
	Finance associate	108	$105,952	$71,000	$175,000
	Senior analyst	83	$109,843	$61,000	$220,000
	Associate	339	$123,649	$54,000	$245,000
	Senior analyst developer	399	$127,460	$80,000	$182,000
	Research associate	138	$162,118	$78,000	$253,000
	Intermediate associate	118	$191,214	$85,000	$300,000
	Vice President	77	$221,484	$110,000	$506,000

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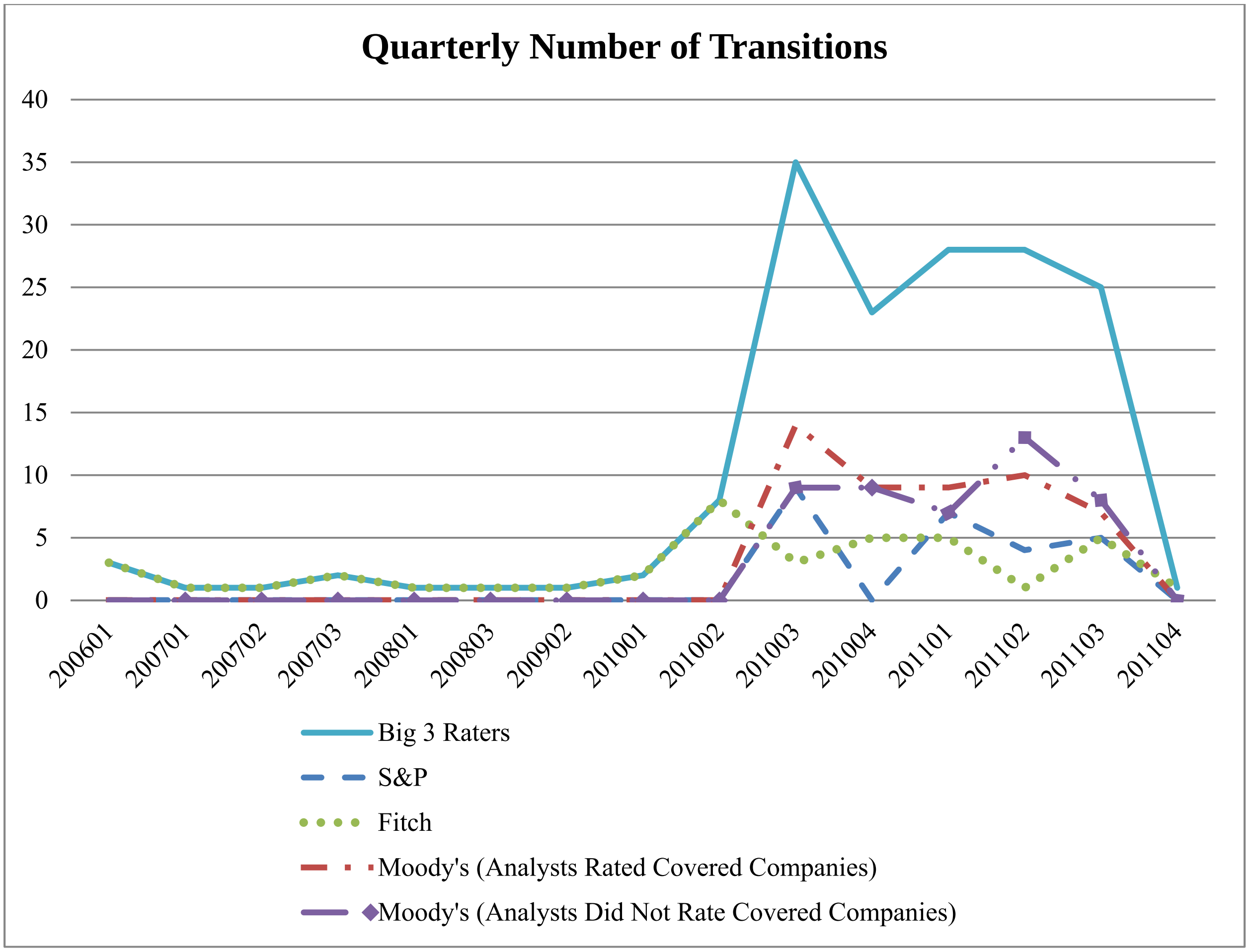

Figure 1: This figure presents the number of analyst transitions from the Big 3 credit rating agencies to covered companies on a quarterly basis from the first quarter of 2006 to the fourth quarter of 2011. When Dodd-Frank became law on July 17, 2010, the mandate required disclosure of employee transitions to covered companies they helped rate over the prior five years.

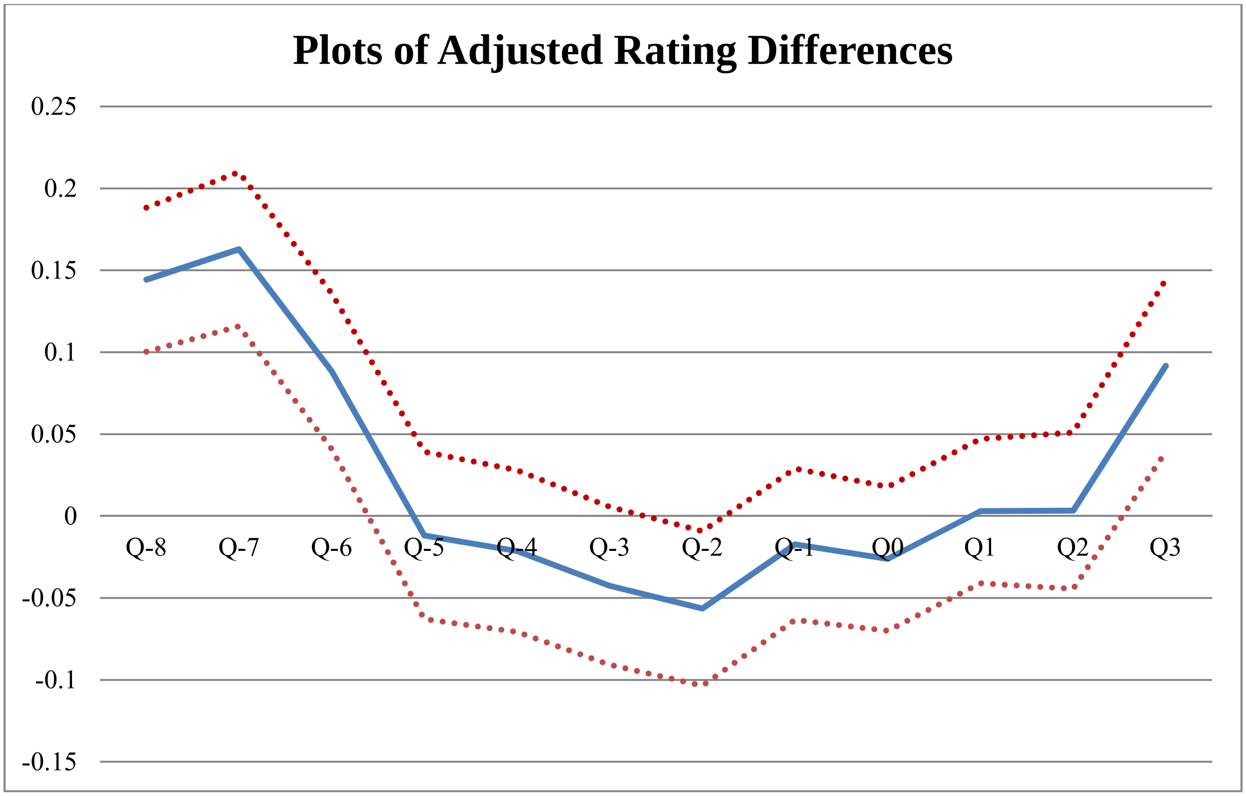

Figure 2: The average calendar year adjusted rating differences between the agency with a transitioning analyst and a benchmark agency without a transitioning analyst. Calendar year adjusted rating differences are the difference between the raw rating differences and the mean difference of the observations in the same calendar year. The adjusted differences are reported by quarter-to-separation from eight quarters to analysts' separation dates. Numeric ratings are decreasing in credit quality (increasing in credit risk); negative differences indicate ratings from transitioning analysts are more favorable than the ones from non-transitioning analysts. We employ Moody's (S&P) as the benchmark agency for transitioning S&P and Fitch (Moody's) analysts. Standard errors are clustered at the issuer level. Dotted lines represent a 95% confidence interval.

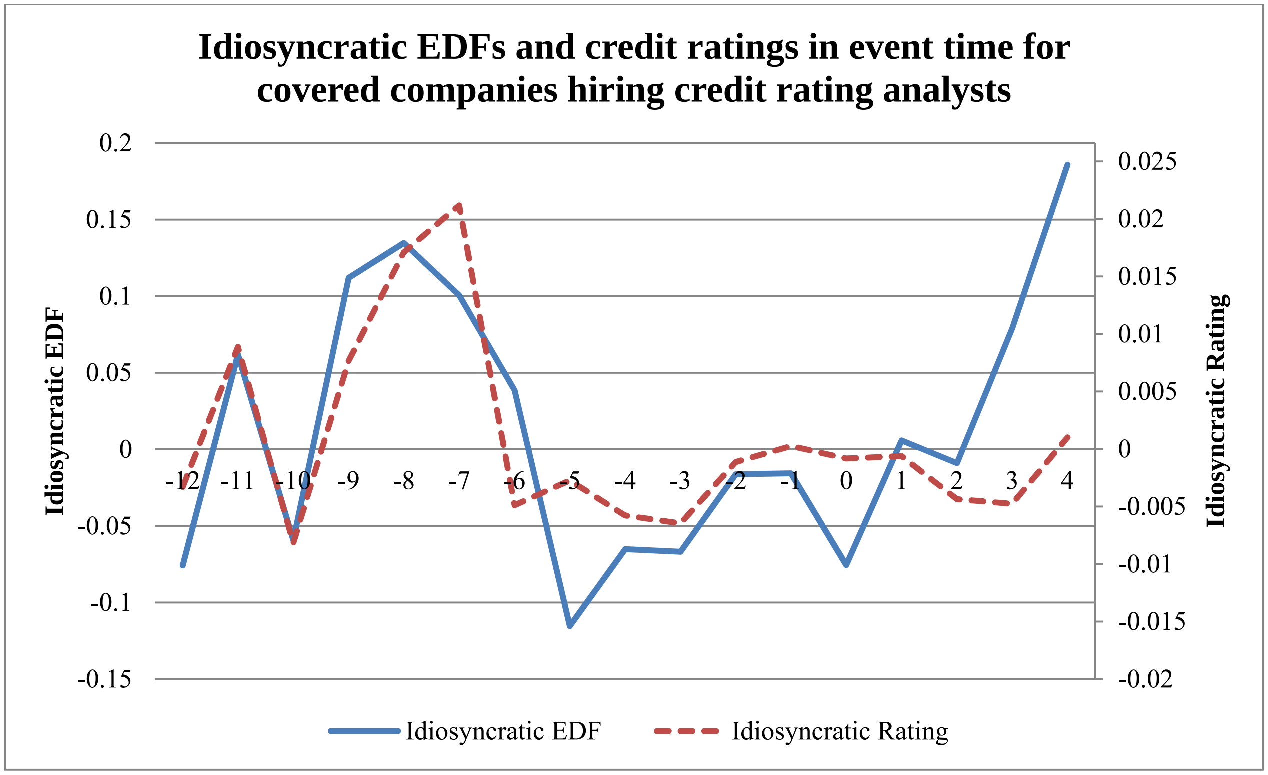

Figure 3: Plots of idiosyncratic credit ratings and idiosyncratic expected default frequency (EDF) derived from the Merton/KMV model over event time. Idiosyncratic credit ratings are measured by the residual of a regression model of credit ratings on indicator variables for calendar years (i.e., year dummies) in an issue-fixed-effect setting. Idiosyncratic EDF are measured in the same way. The sample consists of quarterly observations of ratings from transitioning analysts from 12 quarters prior through four quarters following the analyst separation date. The solid plot is idiosyncratic EDFs. The dotted plot is the idiosyncratic credit ratings.

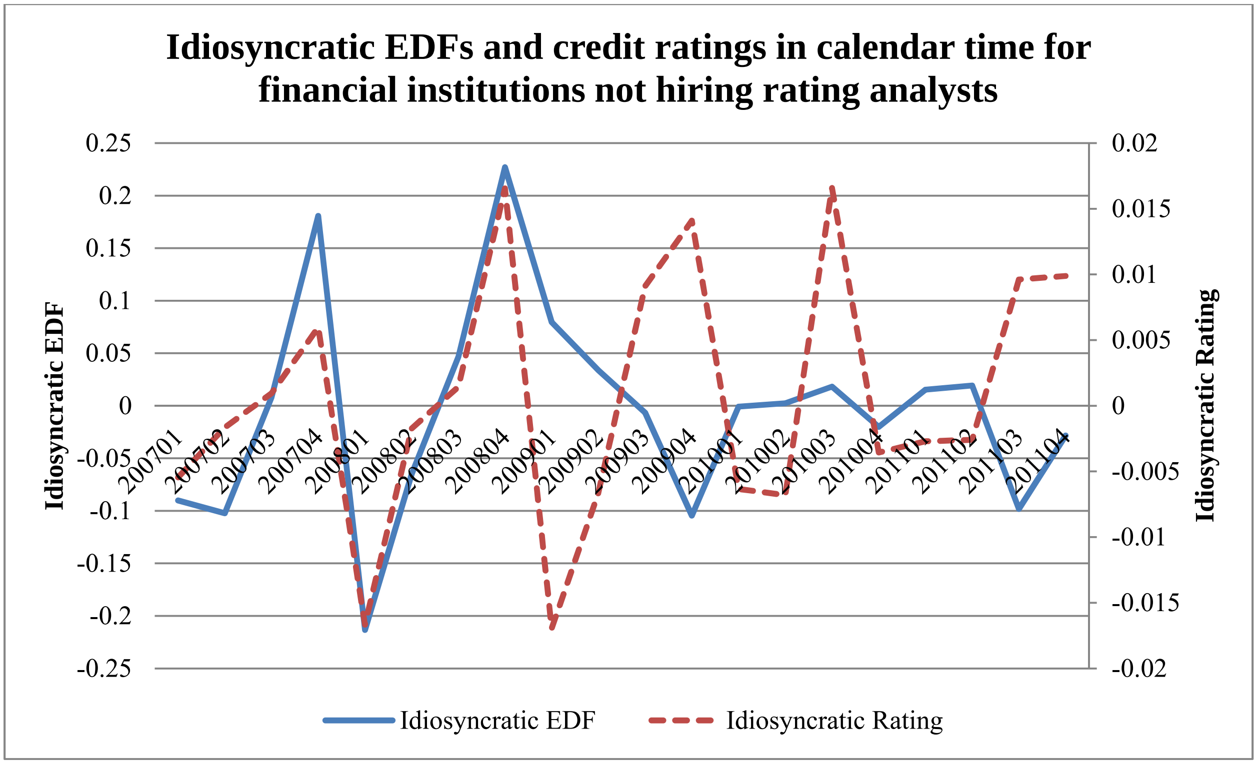

Figure 4: Plots of idiosyncratic credit ratings and idiosyncratic expected default frequency (EDF) derived from the Merton/KMV model over time. The sample consists of quarterly observations of ratings and EDF for financial institutions that do not hire a credit rating analyst. Because there is no event, plots are over calendar time; e.g. 200701 represents Year 2007 Quarter 1. Idiosyncratic credit ratings are measured by the residual of a regression model of credit ratings on indicator variables for calendar years (i.e., year dummies) in an issue-fixed-effect setting. Idiosyncratic EDF are measured in the same way. The sample consists of quarterly observations of ratings from transitioning analysts from 12 quarters prior through four quarters following the analyst separation date. The solid plot is idiosyncratic EDFs. The dotted plot is the idiosyncratic credit ratings.

Table 1 – Employee transitions and covered companies

Panel A reports the transitions of 160 credit rating analysts in our sample from the Big 3 rating agencies (Moody's, S&P, and Fitch) according to reported separation dates by sample quarter. Panel B classifies the covered companies hiring 169 credit rating analysts from any NRSRO.

Panel A: Big 3 Employee Transitions By Sample Quarter

Year Quarter	Big 3 raters	S&P	Fitch	Moody's (Analysts Rated Covered Companies)	Moody's (Analysts Did Not Rate Covered Companies)
200601	3	0	3	0	0
200701	1	0	1	0	0
200702	1	0	1	0	0
200703	2	0	2	0	0
200801	1	0	1	0	0
200803	1	0	1	0	0
200902	1	0	1	0	0
201001	2	0	2	0	0
201002	8	0	8	0	0
201003	35	9	3	14	9
201004	23	0	5	9	9
201101	28	7	5	9	7
201102	25	4	1	10	13
201103	25	5	5	7	8
201104	1	0	1	0	0
Total	160	25	40	49	46

Panel B: Distribution of Covered Companies Hiring NRSRO Analysts

Year Quarter	Banks or Brokers	Asset Managers	Insurers	Others
200601	1	0	0	2
200701	1	0	0	0
200702	2	0	0	0
200703	2	1	0	0
200801	2	0	0	1
200803	1	0	0	1
200902	1	0	1	0
201001	0	1	0	1
201002	4	2	0	2
201003	25	6	3	2
201004	13	6	0	4
201101	18	4	4	2
201102	16	8	1	3
201103	19	3	2	3
201104	0	1	0	0
Total	105	32	11	21

Table 2 – Descriptive Statistics

Panel A displays summary statistics for rating levels from Moody's, Fitch, and S&P. Because numeric ratings are decreasing in credit quality (increasing in credit risk) a smaller number indicates that the rater is more favorable to the issuer. Ratings are on a quarterly basis in the period spanning 12 quarters before each rating analyst's separation date to 4 quarters after. The last column reports differences between the mean of ratings from S&P and Moody's, and from Fitch and S&P, respectively. Standard errors from t-tests are in parentheses. Panel B presents proxies for opacity of covered issuers hiring rating analysts and, separately, of issuers without analyst transitions. Public is a dummy variable that equals 1 if the bond issuer has a public parent company whose stocks are publicly traded in the period of 1990 to 2011; equals 0 otherwise. For the subset of public firms, Capitalization is the book value of ordinary equity. Number of Analysts is the number of equity analysts covering the firm. We calculate Capitalization and Number of Analysts at issuers' parent (bank holding company) level between 2005 and 2010 (20 quarters) to capture the extent of issuers' original information asymmetry before analyst transitions. *** and * indicate significance at the 1% and 10% levels, respectively.

Panel A: Comparison of credit ratings

	Number of Quarterly Observations	Mean	SD	25th Percentile	Median	75th Percentile	Differences in Rating Means
(1) Moody's Ratings	47,663	4.854	2.477	2	5	7	
(2) S&P's Ratings	28,064	4.704	1.182	4	5	6	(2)-(1) -0.150*** (0.016)
(3) Fitch's Ratings	29,657	3.500	1.169	2	4	4	(3)-(2) -1.203*** (0.010)

Panel B: Issuer Opacity

	Covered Issuers (1)		Issuers Without Analyst Transitions (2)		Difference (1) - (2)	
Year	Mean	Median	Mean	Median	Mean	Median
Public	0.90	1.00	0.65	1.00	0.25***	
Capitalization	53,980	43,200	12,667	3,711	41,313***	39,489***
Number of Analysts	10.61	14.63	10.22	9.04	0.38	5.58*

Table 3 – Average Rating Difference Across Event Time

This table presents the average calendar year adjusted rating differences between the agency with a transitioning analyst and a benchmark agency without a transitioning analyst. Calendar year adjusted rating differences are the difference between the raw rating differences and the mean difference of the observations in the same calendar year. The adjusted differences are reported by quarter-to-separation from eight quarters to analysts' separation dates. S&P serves as the benchmark agency for transitioning analysts at Moody's. Moody's serves as the benchmark agency for transitioning analysts at S&P and Fitch. Because numeric ratings are decreasing in credit quality (increasing in credit risk) a positive difference indicates that the rating agency with the transitioning analyst is less favorable to the issuer. Negative (positive) differences of each statistic relative to the separation quarter indicates this is less (more) true in a particular quarter. ***, ** and * indicate averages and differences significantly different from 0 at the 1%, 5% and 10% levels, respectively.

Sample Quarter, Measured Relative to Separation Quarter	Obs.	Mean of Rating Difference	Difference with Separation Quarter
8 Quarters to Separation	3,214	0.14***	0.17***
7 Quarters to Separation	3,014	0.16***	0.18***
6 Quarters to Separation	2,878	0.09***	0.11***
5 Quarters to Separation	2,794	-0.01	0.01
4 Quarters to Separation	2,734	-0.02	0.005
3 Quarters to Separation	2,650	-0.04	-0.02
2 Quarters to Separation	2,575	-0.06**	-0.03
1 Quarter to Separation	2,539	-0.02	0.01
Separation Quarter	2,530	-0.03	
1 Quarter after Separation	2,432	0.003	0.03
2 Quarters after Separation	2,122	0.003	0.03
3 Quarters after Separation	1,807	0.09***	0.12***

Table 4 – Changes in Rating Differences

This table presents fixed-effects OLS regression models. In Models (2) and (3), the dependent variable is the difference in bond ratings between the agency with a transitioning analyst and its benchmark agency. We employ Moody's (S&P) as the benchmark agency for S&P and Fitch (Moody's) analysts. Models (2a) and (3a) employ the subsample of Moody's employees transitioning to issuers they did not rate. In models (2) and (2a) the sample consists of quarterly rating differences from 12 quarters before each analyst's separation date up to the quarter when the separation occurred. "Pre-Transition" equals 1if the observation falls between the 12 quarters before to five quarters before the separation date, and equals 0 if the observation falls within the five quarters the separation date. In models (3) and (3a), the sample consists of quarterly rating differences from five quarters before each analyst's separation date up to four quarter after the separation date. "Transition" is a time period indicator that equals 1 if the observation falls within the five quarters before the separation date and equals 0 if the observation falls within the four quarters after the separation date. Issue Fixed Effects are indicator variables for bond issues. Year Fixed Effects are indicator variables for calendar years. Rating Agency Fixed Effects are indicator variables for S&P's analyst transitions, Moody's analyst transitions, and Fitch's analyst transitions. Standard errors clustered at the issuer level are in parentheses. ***, ** and * indicate coefficients significantly different from 0 at the 1%, 5% and 10% levels, respectively.

	Transitions of Analysts from Moody's, S&P, and Fitch		Moody's Redacted Analyst Transitions	
	Model 2	Model 3	Model 2a	Model 3a
Pre-Transition	0.214**		0.001	
	(0.104)		(0.013)	
Transition		-0.061**		-0.015
		(0.023)		(0.019)
Issue Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Rating Agency Fixed Effects	Yes	Yes	No	No
Constant	0.544*	0.807***	0.498***	0.452***
	(0.294)	(0.060)	(0.007)	(0.036)
Observations	39,450	19,746	3,718	1,968
Within-Issue R-squared	0.057	0.337	0.353	0.016

Table 5 – Changes in Rating Information Content

This table presents fixed-effects OLS regression models. The dependent variable is the numerical value of bond ratings from an agency with a transitioning analyst. EDF is the expected default frequency derived from the Merton/KMV model described in Appendix B. In model (5) the sample consists of quarterly rating differences from 12 quarters before each analyst's separation date up to the quarter when the separation occurred. "Pre-transition" equals 1if the observation falls between the 12 quarters before to six quarters before the separation date, and equals 0 if the observation falls within the five quarters before and on the separation date. In model (6), the sample consists of quarterly rating differences from five quarters before each analyst's separation date up to four quarter after the separation date. "Transition" equals 1 if the observation falls within the five quarters before and on the separation date and equals 0 if the observation falls within the four quarters after the separation date. In model (7) the sample consists of quarterly rating differences from 12 quarters before each analyst's separation date to six quarters before each analyst's separation date, and the four quarters after the separation date. "Post-transition" equals 1 if the observation the observation falls within the four quarters after the separation date and equals 0 otherwise. Issue Fixed Effects are indicator variables for bond issues. Year Fixed Effects are indicator variables for calendar years. Rating Agency Fixed Effects are indicator variables for S&P's analyst transitions, Moody's analyst transitions, and Fitch's analyst transitions. Standard errors clustered at the issuer level are in parentheses. ***, ** and * indicate coefficients significantly different from 0 at the 1%, 5% and 10% levels, respectively.

	Model 5	Model 6	Model 7
EDF	-0.222	0.109*	0.887***
	(0.251)	(0.055)	(0.204)
Pre-Transition * EDF	1.002***		
	(0.290)		
Pre-Transition	-0.601**		
	(0.217)		
Transition * EDF		-0.212***	
		-0.062	
Transition		0.049	
		-0.042	
Post-Transition * EDF			-0.869***
			(0.315)
Post-Transition			-0.0617
			(0.283)
Issue Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Rating Agency Fixed Effects	Yes	Yes	Yes
Constant	3.719***	4.397***	4.141***
	(0.430)	(0.250)	(0.323)
Observations	45,922	24,885	20,864
R-squared	0.527	0.607	0.604

Table 6 – Summary Statistics for New Bond Issuance

This table presents the number and amount of new bond issues for issuers whose bonds are covered by transitioning analysts. Summary statistics are reported by quarter-to-separation from eight quarters to analysts' separation dates. ***, ** and * indicate averages and differences significantly different from 0 at the 1%, 5% and 10% levels, respectively.

	Number of New Bond Issues		Amount of New Bond Issues ($000)	
Sample Quarter, Measured Relative to Separation Quarter	Mean	Difference with Separation Quarter	Mean	Difference with Separation Quarter
8 Quarters to Separation	1.185	0.123	186,958	128,011***
7 Quarters to Separation	1.042	-0.02	135,358	76,411**
6 Quarters to Separation	0.999	-0.063	117,478	58,531**
5 Quarters to Separation	1.102	0.04	95,772	36,825
4 Quarters to Separation	1.268	0.206	81,227	22,280
3 Quarters to Separation	1.223	0.161	75,757	16,805
2 Quarters to Separation	1.312	0.25	90,204	31,257
1 Quarter to Separation	1.203	0.141	64,034	5,087
Separation Quarter	1.062		58,947	
1 Quarter after Separation	0.797	-0.265	56,811	-2,135
2 Quarters after Separation	0.805	-0.257	53,724	-5,223

Table 7 – Summary Statistics of Watchlist Provisions

This table presents summary statistics for the incidence of rating agencies' Watchlist provisions. The number under the column Transitioning Analysts denotes the number of quarters before an analyst's separation date when a Watchlist was last placed by an agency with a transitioning analyst. The number under the column Benchmark Analysts denotes the number of quarters before an analyst's separation date when a Watchlist was last placed by the benchmark agency. We employ Moody's (S&P) as the benchmark agency for transitioning S&P and Fitch (Moody's) analysts. Panel A reports negative Watchlist provisions and Panel B reports positive Watchlist provisions.

Panel A: Negative Watchlist		
	Transitioning Analysts	Benchmark Analysts
Mean	14.44	12.97
Median	11	11
25th Percentile	17	15
75th Percentile	8	11

Panel B: Positive Watchlist		
	Transitioning Analysts	Benchmark Analysts
Mean	19.25	20.68
Median	20	24
25th Percentile	22	29
75th Percentile	19	8

Table 8 – Depository Institutions, Derivatives Trading and CDO Underwriting Activity

This table presents the depository institution status (Panel A), bank trading and derivatives activities (Panel B), and CDO underwriting activities (Panel C) separately for 308 covered companies (including parents and subsidiaries of the firms identified by the SEC) and a control group of 670 financial institutions that issue bonds but do not hire rating analysts. In Panel A, Depository Institution is a dummy that equals one if the issuer (or the bank holding company of an issuer) is a depository institution, and equals 0 otherwise. In Panel B, Percentage in Top 25 is the percentage of issuers whose bank holding companies are among the Top 25 banks in derivatives activities ranked by the notional amount of derivative contracts. Derivatives to Total Assets Ratio is the ratio of the amount of derivative contracts to total assets, conditional on the issuer being among the top 25 banks in derivatives in the given year. Derivative activities data is collected from the quarterly report on bank trading and derivatives activities from the Comptroller of the Currency Administrator of National Banks. Panel B reports information in the fourth quarter of each year. In Panel C, the first section reports yearly statistics and the second section reports statistics aggregated into sub-periods 2000-2003 and 2004-2007. The Amount of CDO Underwritten is the principal value (in U.S. million dollars). The Market Share of CDO Underwritten is the amount of CDOs underwritten by an individual issuer scaled by the total amount of CDO underwritten by all issuers in the same year. Both variables are calculated at issuers' parent (bank holding company) level. CDO underwriting information is collected from the ABS database managed by J.P. Morgan's Asset-Backed Alert. In Panel A and Panel B, *** and ** indicates differences significantly different from 0 at the 1% and 5% level, respectively. In Panel C, all pairwise differences are significantly different from 0 at the 1% level.

Panel A: Depository Institutions

	Covered Companies Hiring Credit Rating Analysts (1)		Control Companies (2)		Differences (2)-(1)
	Mean	Median	Mean	Median	Mean
Depository Institution	0.40	0	0.25	0	-0.15***

Panel B: Derivatives Trading Activity									
	Covered Companies Hiring Credit Rating Analysts			Control Companies			Difference		
	Percentage in Top 25	Derivatives to Total Assets Ratio		Percentage in Top 25	Derivatives to Total Assets Ratio		(1)-(4)	(2)-(5)	(3)-(6)
Year	(1)	Mean (2)	Median (3)	(4)	Mean (5)	Median (6)			
2000	27.60%	5.60	2.78	5.95%	2.92	0.95	+***	+**	+**
2001	34.09%	10.23	5.79	6.11%	2.20	1.10	+***	+***	+***
2002	40.26%	10.28	6.40	6.11%	1.75	0.95	+***	+***	+***
2003	40.26%	12.69	6.58	5.81%	2.04	1.24	+***	+***	+***
2004	40.26%	12.68	7.95	5.22%	1.58	0.99	+***	+***	+***
2005	40.26%	14.37	7.65	5.20%	1.65	1.10	+***	+***	+***
2006	40.26%	15.33	10.60	5.50%	1.61	0.97	+***	+***	+***
2007	42.21%	15.03	6.68	4.92%	1.70	1.28	+***	+***	+***
2008	51.95%	18.00	4.27	4.32%	1.31	1.01	+***	+**	+***
2009	43.41%	33.66	4.07	4.62%	1.36	1.11	+***	+*	+***
2010	43.41%	37.33	5.48	4.32%	1.51	0.76	+***	+**	+***
2011	43.41%	36.17	20.98	4.47%	1.28	0.82	+***	+**	+***

Panel C: CDO Underwriting Activity								
	Covered Companies Hiring Credit Rating Analysts				Control Companies			
	Amount of CDO Underwritten ($Mil)		Market Share of CDO Underwritten		Amount of CDO Underwritten ($Mil)		Market Share of CDO Underwritten	
Year	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2000	1,867.61	828.70	2.39%	1.06%	35.87	0	0.05%	0
2001	2,271.84	156.25	2.79%	0.19%	29.48	0	0.04%	0
2002	2,653.74	260.35	3.09%	0.30%	6.19	0	0.01%	0
2003	2,391.56	110.63	2.74%	0.13%	7.22	0	0.01%	0
2004	3,459.75	46.50	2.73%	0.04%	12.28	0	0.01%	0
2005	7,253.72	525.80	2.87%	0.21%	28.57	0	0.01%	0
2006	13,623.15	4,798.85	2.85%	1.00%	32.04	0	0.01%	0
2007	11,606.35	1,055.20	2.84%	0.26%	51.06	0	0.01%	0
Aggregate								
2000-2003	6,574.67	2,245.40	8.01%	2.57%	1,769.43	0	2.13%	0
2004-2007	26,895.16	5,542.90	9.97%	2.19%	3,348.94	263.15	0.85%	0.07%

Table 9 – Changes in Rating Differences and Rating Information Content (Issuer-Level)

This table presents fixed-effects OLS regression models, using issuer-transition level observations. In models (2) and (3), the dependent variable is the difference in the median bond ratings between the agency with a transitioning analyst and its benchmark agency for each issuer-transition pair. We employ Moody's (S&P) as the benchmark agency for S&P and Fitch (Moody's) analysts. In models (5), (6) and (7), the dependent variable is the median of the numerical value of bond ratings from an agency with a transitioning analyst for each issuer-transition pair. EDF is the median of the expected default frequency for each issuer-transition pair, derived from the Merton/KMV model described in Appendix B. In models (2) and (5) the sample consists of quarterly rating differences from 12 quarters before each analyst's separation date up to the quarter when the separation occurred. "Pre-Transition" equals 1if the observation falls between the 12 quarters before to five quarters before the separation date, and equals 0 if the observation falls within the five quarters the separation date. In models (3) and (6) the sample consists of quarterly rating differences from five quarters before each analyst's separation date up to four quarter after the separation date. "Transition" is a time period indicator that equals 1 if the observation falls within the five quarters before the separation date and equals 0 if the observation falls within the four quarters after the separation date. In model (7) the sample consists of quarterly rating differences from 12 quarters before each analyst's separation date to five quarters before each analyst's separation date, and from the quarter when the separation occurred to four quarter after the separation date. "Post-Transition" equals 1if the observation the observation falls within the four quarters after the separation date and equals 0 otherwise. Issue-Transition Fixed Effects are indicator variables for each issuer-transition pair. Year Fixed Effects are indicator variables for calendar years. Standard errors clustered at the issuer level are in parentheses. ***, ** and * indicate coefficients significantly different from 0 at the 1%, 5% and 10% levels, respectively.

Panel A: Rating Differences

	Model 2	Model 3
Pre-Transition	0.142**	
	(0.062)	
Transition		-0.056*
		(0.030)
Issuer-Transition Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Constant	0.604**	0.201***
	(0.232)	(0.036)
Observations	734	594
Within-Issuer-Transition R-squared	0.027	0.012

Panel B: Rating Information Content

	Model 5	Model 6	Model 7
EDF	-0.165	0.098	0.518***
	(0.289)	(0.126)	(0.143)
Pre-Transition * EDF	0.623**		
	(0.276)		
Pre- Transition	-0.370**		
	(0.152)		
Transition * EDF		-0.081	
		(0.074)	
Transition		-0.002	
		(0.009)	
Post- Transition * EDF			-0.993***
			(0.344)
Post- Transition			-0.041
			(0.155)
Issuer-Transition Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Constant	3.560***	4.239***	4.680***
	(0.271)	(0.042)	(0.185)
Observations	964	648	654
Within-Issuer-Transition R-squared	0.440	0.011	0.479