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Herding Behavior and Rating Convergence among Credit Rating Agencies: Evidence from the Subprime Crisis*

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Abstract. This article examines how credit rating agencies (CRAs) react to rating decisions on mortgage-backed securities by rival agencies in the aftermath of the subprime crisis. While Fitch is on average the first mover, Moody's and S&P perform more timely downgrades given a downgrade or a more severe evaluation by a CRA other than Fitch, and they also influence Fitch more than they are influenced by it. Rating convergence is more likely when Fitch rather than the rival has to adjust its evaluation downwards. Our results support theoretical predictions on the role of reputation in explaining herding behavior among CRAs.

JEL Classification: G01, G14, G24, G38

1. Introduction

The credit rating agency (CRA) industry has often been identified as a major contributor to the spectacular boom and bust of the subprime mortgage-backed securities market in the 2000s for having assigned inflated ratings to increase their revenues (e.g., White, 2010; Bolton, Freixas, and Shapiro, 2012). The CRAs responded to this accusation by arguing that such behavior puts their reputation at risk, and since reputation is the most valuable asset that a CRA has over the longer term, such short-term opportunism is a very weak incentive. Given the oligopolistic nature of the rating industry, CRAs are arguably concerned with their reputation relative to each other. This can lead them to take into account evaluations by rival CRAs in their ratings—a phenomenon generally referred to as *herding* (e.g., Devenow and Welch, 1996).

Using a large sample of subprime mortgage-backed securities issued between 1992 and 2007, we investigate herding behavior and rating

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convergence among CRAs during the recent subprime crisis. The theoretical literature predicts that analysts with stronger reputational concerns have more acute incentives to herd (Scharfstein and Stein, 1990), and that reputational concerns are magnified for those CRAs with lower reputational capital (Mathis, McAndrews, and Rochet, 2009). As such, a CRA with a lower reputation is expected to be more heavily influenced by the behavior of other agencies. Moreover, Mariano (2012) shows that the strength of herding behavior is increasing with the reputation of the first mover. Thus, a CRA with lower reputational capital is expected to exercise a weaker influence over other rating agencies.

To assess whether, and to what extent, the above reputational and herding effects hold, we focus on the behavior of the so-called "big three" rating agencies (Moody's, Standard and Poor's and Fitch) and exploit the differences in market power and reputation of Moody's and S&P, on the one hand, versus Fitch on the other. Specifically, given that Fitch is reasonably considered to be of lower reputation than either Moody's or S&P,[1] we predict that the two main CRAs are more influenced by each other than by Fitch, and that they influence the latter more than the other way around.

To operationalize our analysis, we carefully construct a dataset of Home Equity Loan (HEL) securities rated by either Moody's, S&P, or Fitch, and subsequently downgraded by at least one of these CRAs between June 1 2007—before the advent of the crisis—and July 29 2011. We use Cox proportional hazard models to estimate how the presence of rating actions by, and rating disagreements with, rival CRAs affect the downgrade intensity of each agency. Similar to Güttler (2011), our goal is to compare relative differences across CRAs regarding the timing of rating actions and rating convergence, rather than to compare the timing of downgrades against some absolute benchmark.

Our key findings can be readily summarized. While Fitch, on average, is the first mover after the onset of the crisis, we show that, after controlling for several characteristics at the loan, tranche and deal level, the downgrade intensity of both Moody's and S&P is significantly more affected by the presence of a downgrade by each other (as main rivals), than by Fitch. Further, S&P and (especially) Moody's, on average, more strongly influence the timing of rating revisions made by Fitch than the other way around. These results are confirmed when inclusions in a negative watchlist are also taken into account and, moreover, are robust to a series of meaningful robustness checks. Additionally, we find that neither Moody's nor S&P

[1] Our treatment of Fitch as a lower reputation CRA compared to its main rivals is explained and justified in Section 2.2.

perform more timely downgrades in the presence of a lower rating by Fitch, while the downgrade intensities of all three CRAs are increased by the presence of a lower rating by either Moody's or S&P.

Finally, based on multinomial logit model estimation, we show that the likelihood of observing aligned rating evaluations by July 2011 on securities jointly rated by Moody's (or S&P) and Fitch is significantly higher if Moody's (or S&P), rather than Fitch, assigns the lower rating before the onset of the crisis—suggesting that Fitch is more keen to adjust its ratings downward to align with those of Moody's and S&P, rather than the other way around. The effect of split ratings before the crisis, on the likelihood of aligned evaluations by July 2011, is instead insensitive to the direction of the disagreement on tranches jointly rated by Moody's and S&P.

Overall, our results are consistent with the idea that different CRAs influence, and are influenced by, other agencies to varying degrees. In particular, the agency with the weakest reputation appears to be the least influential on, and most influenced by, rival CRAs—as predicted by theoretical models on herding behavior. The more reputable CRAs (Moody's and S&P) appear, instead, to influence each other in a symmetric fashion.

The subprime crisis is an ideal setting to investigate the herding behavior of CRAs for several reasons. First, the crisis affected thousands of similar securities at the same time, allowing us to study the rating revision activity of CRAs on many issues using a common time framework. Second, the absence of a continuous marking-to-market and the difficulty to assess credit quality of structured products magnifies the potential role played by competitors' evaluations as a reference point. Third, reputational concerns are in general stronger during a recession (Bar-Isaac and Shapiro, 2013). Finally, the large number of securities in need of a rating revision, and their complexity and opacity, is likely to have increased the importance of rating actions by rival CRAs as a source of information over the evolution of credit quality (as it is less feasible for CRAs to privately revise all assigned ratings at the same time).

Our article relates to different strands of literature. First, we contribute to the literature on CRA behavior in the context of the subprime crisis. This literature has mainly focused on empirical evidence for rating inflation and rating shopping that occurred before the onset of the crisis (Aschcraft, Goldsmith-Pinkham, and Vickery, 2010; Benmelech and Dlugosz, 2010; Griffin and Tang, 2012; Griffin, Nickerson, and Tang, 2013; He, Qian, and Strahan, 2012), and on the informational content of ratings (Adelino, 2009; Mählmann, 2012). While some of these studies assess the magnitude and probability of downgrades that followed, little or no real attention has been paid to the timing of those rating actions.

A second strand of related literature assesses the timing of rating revisions and the interdependence of rating actions by different CRAs, mainly in the context of corporate bonds (Covitz and Harrison, 2003; Güttler and Wahrenburg, 2007; Güttler, 2011). Our main contributions to this literature are three-fold. First, we assess CRA rating actions on structured finance products, instead of corporate bonds, during the subprime crisis. Second, while the bulk of the previous literature focuses on Moody's and S&P only, we include Fitch in our analysis. Indeed, this uneven three-way focus is a particularly salient dimension of our analysis. As our results show, there are significant differences in terms of herding behavior between the smallest of the three main CRAs, on the one hand, and Moody's and S&P on the other. Third, we provide a rationale for these differences, building on theoretical models such as Stolper (2009) and Mariano (2012), and focus on the role of reputation and informational cascades in explaining herding behavior for CRAs. Finally, our results contribute to the extant empirical literature investigating herding behavior of financial analysts in general, including Hong, Kubik, and Solomon (2000) and Welch (2000).

Our article proceeds as follows. Section 2 provides a brief introduction to the subprime mortgage-backed securities market and a literature review which motivates our core empirical predictions. In Section 3, we outline the sampling process and the dataset. In Section 4, the empirical analyses are presented and discussed. Section 5 closes with some final remarks and conclusions.

2. Background, Literature Review, and Empirical Predictions

2.1 A PRIMER ON SUBPRIME MORTGAGE-BACKED SECURITIES

Subprime mortgage-backed securities are a particular class of asset-backed securities (ABS) backed by residential mortgages. ABS are obligations with interest and principal repayments derived from, and collateralized by, a specific pool of underlying assets. In its most simple form, an ABS is simply an agreement to transfer the cash flows generated by the collateral to investors in exchange for an upfront payment. This form of ABS is referred to as a pass-through security. ABS, however, are generally more complex. They are usually split into different security categories, called "tranches", and while all rely on the same collateral, the ABS deal can be structured such that each tranche differs from the others in a variety of ways (including in terms of credit risk, duration, maturity, and prepayment risk).

The most common ABS structure divides tranches by different levels of seniority. In such cases, three levels of tranches are usually formed: Senior, Mezzanine, and Subordinated (the latter also called Junior tranches).

Whenever a loss on the underlying assets occurs, Subordinated tranches are hit first and absorb the loss. When Subordinated tranches have defaulted entirely, Mezzanine tranches start absorbing the losses, and so on. Thus, at the time of issuance, the nominal value of the collateral for a Senior tranche is higher than the nominal value of the tranche itself. The value of the collateral in excess of the value of a tranche is called the credit support of that tranche, and is usually expressed as a percentage of the tranche value. While subordinated tranches typically have no credit support by the time they are issued, as a form of credit enhancement, sometimes not all the collateral is used to back the issue. As a result, even junior tranches can have some initial credit support.

Deals can also be structured to allow different tranches to pay with different timing compared to the collateral, or to use only certain cash flows of the collateral for payments. For example, a tranche can pay out investors faster than its collateral (accelerated security) or more slowly (nonaccelerated security)—thus accommodating different exposures to prepayment risk. With a similar logic, a tranche can start repaying its principal only after other tranches have paid theirs down to zero (sequential tranches). Some tranches can also derive their payments only from interest paid on the collateral (interest only, or IO), while others are only paid out of principal repayments (principal only, or PO).

ABS are issued via a standard securitization process. Originators create the assets to be used as collateral. In the case of residential mortgages, originators provide loans to mortgagees. Then, a depositor collects the assets to be used as collateral and creates a Special Purpose Vehicle (SPV), which is the final issuer of the ABS. The use of a SPV for the issuance guarantees a clear division between the liabilities of the depositors and those of the issuer. Before issuing the ABS, one or more CRAs are contacted to rate the issue. CRAs discuss the deal and, after collecting the required information, provide the issuer with a "shadow rating" (Skreta and Veldkamp, 2009). In contrast to traditional issuances, structured finance deals are subject to changes before issuance, and thus it is possible for the issuer to decide to partially modify it to achieve a desired rating evaluation. Moreover, the issuer can either decide to make the rating public, thus paying the CRA for its evaluation, or to refuse it, and pay a contract-breaking fee and potentially ask another CRA for an evaluation (Griffin and Tang, 2012). Once a rating is made official, the security can be placed and the rating CRAs are assumed to still be monitoring the deal. As ratings are unconditional opinions on credit quality through the business cycle, CRAs are expected to adjust their evaluations when the expected default probability (or expected loss) is estimated to have changed materially.

2.2 LITERATURE REVIEW

Generally, the literature suggests that, other things being equal, there could be an upward bias in ratings assigned by CRAs due to: the presence of naïve investors (Bolton, Freixas, and Shapiro, 2012); asset complexity (Mathis, McAndrews, and Rochet, 2009); regulatory use of ratings (Opp, Opp, and Harris, 2013) and ratings shopping (Skreta and Veldkamp, 2009). Indeed, several studies provide compelling empirical evidence of this phenomenon (e.g., Ashcraft, Goldsmith-Pinkham, and Vickery, 2010; Benmelech and Dlugosz, 2010; He, Qian, and Strahan, 2012; Griffin and Tang, 2012).

There could also be a "conformity" bias in rating agencies evaluation (Kuhner, 2001)—that is, CRAs have incentives to collude and herd in their evaluations, and thus are not providing the market with truly independent evaluations. Theoretical models on the behavior of economic agents in general have highlighted three possible effects to justify rational herding (for a review of this literature, see Devenow and Welch, 1996). First, herding can arise because the payoff associated with a certain action can increase with the number of agents acting in a similar manner. Second, agents can infer new information from the divergent actions of other agents and incorporate it into their decisions (Welch, 1992). Finally, agents might decide to "hide in the herd" to reduce the likelihood of being punished in case their decision proves, *ex-post*, to be poor (Scharfstein and Stein, 1990).

The latter two effects are particularly relevant for explaining herding behavior among CRAs. While, in theory, rating agencies do not know what rating their rivals will assign before the security is issued,[2] once ratings and rating changes become publicly available information, other CRAs might decide to incorporate this into their own evaluations, especially when public consensus about credit quality is low (Mariano, 2012). As for the role of reputation, Stolper (2009) shows that CRAs have a strong incentive to align their evaluations, especially when they are rating complex and opaque products such as ABS. The rationale for this is that by aligning evaluations, this makes it difficult, in the case of unanticipated defaults of highly rated securities, to distinguish whether CRAs consciously assigned inflated ratings or whether defaults are triggered by exogenous, unpredictable shocks. In contrast, a CRA failing to recognize the risk of one security, while other agencies do so, can be easily singled out and put its reputational

[2] Griffin, Nickerson, and Tang (2013) provide empirical evidence that Moody's and S&P make stronger upward adjustments of initial evaluations beyond their quantitative model predictions when the main rival's model is expected to be less severe. This suggests that CRAs might be taking rivals' assessments into account even before a security is issued.

capital at risk.[3] Thus, CRAs have incentives to herd to protect their reputational capital, and this incentive is especially strong when rating complex structured finance products.

2.3 EMPIRICAL PREDICTIONS

To the extent that reputation and signaling of new information play key roles in explaining herding behavior as the theoretical literature suggests, some expectations can be developed regarding relative differences in this regard across different rating agencies. Mathis, McAndrews, and Rochet (2009) predict that reputational concerns are stronger for rating agencies with lower reputational capital, while Mariano (2012) argues that the likelihood of herding among CRAs increase with the reputation of the first mover, as its rating is thought to embed superior private information. As such, rating agencies are expected to be influenced more by decisions of rivals with a higher reputation, while a more reputable CRA is expected to influence the decisions of an agency with a relatively lower reputation.

From an empirical point of view, based on these arguments, we are interested in assessing how the timing of rating revisions is influenced by downgrades performed by other agencies and/or by the presence of discordant ratings. Moreover, to provide further evidence of different incentives toward rating convergence for alternative CRAs, we investigate whether the probability of rating convergence differs with the identity of the agency assigning the more severe evaluation.

There are three sound reasons to consider Fitch as having a lower reputation than either Moody's or S&P. First, Fitch has a lower market share: ratings by Fitch are estimated to be around 15% of all outstanding ratings against a market share of around 40% each for Moody's and S&P (White, 2010). Second, rating actions by Fitch have a weaker market impact: Norden and Weber (2004) document that downgrades by Fitch have a much weaker impact on stock returns and on Credit Default Swap (CDS) spreads compared to downgrades by Moody's and S&P. Together, these comparative findings suggest that (other things equal) markets assign a lower weighting to the information conveyed by Fitch's evaluations. Finally, ratings by Fitch are less accurate: Gaillard (2013) shows that the accuracy ratio performance of Fitch ratings on sovereign bonds is 1–2% lower than the counterpart performance for Moody's and S&P (both over 1- and 5-year

[3] Following a similar logic, Bar-Isaac and Shapiro (2013) also model a situation where misapplied evaluations are punished by investors in the presence of a second, discordant evaluation by a rival agency.

horizons). As such, by synthesizing the theory and various coalescing arguments from the literature, we propose three basic empirical predictions:

P1: The timing of downgrades by either Moody's or S&P is more influenced by rating actions taken by the other main rival than those taken by Fitch.

P2: Moody's and S&P exhibit a stronger tendency toward rating convergence with each other than with Fitch.

P3: Fitch's rating actions tend to be influenced more by Moody's or S&P actions, compared to the (lesser) influence of Fitch's rating actions on Moody's or S&P.

3. Data and Variables

3.1 SAMPLE

Our goal is to analyze CRA rating revision activity on nonprime mortgage-backed securities in the aftermath of the 2007 crisis. Accordingly, our sample is based on a search in Bloomberg of all US ABS Home Equity Loan (HEL) tranches[4] that experienced a downgrade and/or have been placed on a watchlist for a future downgrade by either Moody's, S&P, or Fitch between June 1 2007 (signifying the advent of the crisis)[5] and July 29 2011. We focus on the HEL category because it was both the most relevant and most affected group during the crisis. According to Benmelech and Dlugosz (2010), HEL accounted for 54% and 26% of all downgrades of structured finance issues in 2007 and 2008, respectively, and represents on average 54% of collateral pools of ABS Collateralized Debt Obligations (CDOs) issued between 2005 and 2007. By focusing on one category, we are able to analyze a predominantly homogenous sample of structured finance products while controlling for several characteristics of each tranche and deal likely to moderate the phenomena under study.[6]

[4] Indexed in Bloomberg as ABS/CMO HOMEEQ category, US market.

[5] On June 21, 2007, Merrill Lynch conducted a selling audit of its $850 million share in two Bear Sterns funds, mainly invested in structured finance products. Despite several liquidity injections into the two funds by Bear Sterns, JP Morgan and others, no buyer was found—forcing a severe write down of assets.

[6] Choosing a homogenous class of assets is also important because, as shown empirically by Cornaggia, Cornaggia, and Hund (2014), despite the use of the same rating scale across all products, ratings assigned by the same CRA to different types of assets exhibit systematic differences.

As shown in Table I, we identify 9,242 tranches, representing 1,898 deals, issued before June 1 2007 and downgraded/watchlisted during the period under analysis. To provide a basis of comparison for the intensity of the rating revision activity occurring since the advent of the crisis, a search on Bloomberg for downgrades of US HEL securities occurring between January 1 2000 and June 1 2007 returned just 570 distinct tranches, half of which (276) were downgraded during the first 5 months of 2007. This statistic is in line with those reported by Ashcraft and Schuermann (2008), who document that downgrades occurring in the first 7 months of 2007 account for half of all downgrades in the history of HEL securities up to that point.

Table I reports the distribution of our sample and some relevant statistics on the timing of rating revisions since the crisis started. Consistent with the general pattern of market growth, the number of sampled tranches increases over years of issuance, while only 552 tranches were issued between 1992 (the oldest vintage present in our sample) and 2000, with 2,282 tranches in 2005 (this vintage alone accounts for almost a quarter of our sample).

Over the whole sample, S&P is the most represented agency, rating 8,725 tranches (approximately 94%); Moody's evaluation is present for 8,059 tranches (87%), while Fitch is a clear third with 5,202 (56%) rated issues. In the context of our sample, it is interesting to observe how market shares across the three agencies have evolved over time. In 2001, Moody's was clearly the "leading" CRA, rating almost 93% of the tranches issued that year, with S&P a clear second (rating 82%), and Fitch evaluations being present for about two-thirds of the tranches. While in the 1990s, Fitch had a similar market share as Moody's or S&P, over the years its presence in the market has dramatically fallen. By the beginning of 2007, it was rating only 25% of newly issued tranches. Over the years leading up to the market crisis, S&P overtook Moody's, rating about 97% of tranches issued in 2006, while the latter dropped back to 88%. This picture is consistent with that presented by Benmelech and Dlugosz (2010), who find that S&P was more likely subject to rating shopping than its peers. Rating shopping in general seems to have become more common in the years leading up to the crisis: from 2001 to the first months of 2007, the share of tranches rated by only one CRA increased from around 4.3% to 12.4% (with a low of 1% in 2003), while the share of tranches rated by all the three main CRAs dropped from 42.4% to 21.9% (with a high of 75%). These statistics highlight the importance of controlling for the effective number of ratings for each security in our study.

Panel B reports the timing of rating actions for tranches effectively downgraded/included in a negative watchlist by each CRA before August

Table I. Sample distribution and descriptive statistics of rating revision activity

This table reports the distribution of our sample and relevant descriptive statistics for our main dependent variables. Vintage is the year of settlement of the deal; tranches (deals) is the number of HEL tranches (deals) in our sample. % rated by Moody's (S&P, Fitch) report the percentage of tranches rated by Moody's (S&P, Fitch) as at June 1 2007. No. of rating agencies identify the percentage of tranches rated by one, two or three CRAs. *Days to First Downgrade* are the calendar days elapsed since June 1 2007 to the first downgrade by each CRA for tranches effectively downgraded by July 29 2011. *Days to First Downward Rating Revision* are the calendar days elapsed since June 1 2007 to the first downgrade or negative watchlist inclusion (whichever occurs first) by each CRA for tranches effectively downgraded/watchlisted by July 29 2011. In Panel C, for each pair of CRAs (A) and (B) is reported the share of jointly rated tranches downgraded (*First downgrade*) or receiving a downward rating revision (*First Down. Rating Revision*) faster by agency (A) or (B). Ties refers to rating actions occurring the same day. Wilcoxon z is the z-statistic for a Wilcoxon signed-rank test on the median difference in the timing of rating revisions by two CRAs being equal to 0. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: sample distribution by year of issuance and rating agencies

			% rated by			No. of rating agencies		
Vintage	Tranche	Deals	Moody's	S&P	Fitch	One	Two	Three
1992–2000	552	227	75.54%	66.49%	73.91%	8.85%	66.33%	24.82%
2001	255	96	92.55%	81.96%	63.53%	4.32%	53.33%	42.35%
2002	437	135	95.19%	90.39%	66.13%	4.35%	39.59%	56.06%
2003	990	219	96.16%	98.79%	79.39%	1.12%	23.43%	75.45%
2004	1,591	287	86.11%	98.00%	66.56%	6.48%	36.20%	57.32%
2005	2,282	339	84.14%	95.00%	61.79%	4.38%	49.87%	45.75%
2006	2,071	405	87.69%	96.76%	39.74%	9.27%	57.27%	33.46%
2007 (first 5 months)	1,064	190	87.59%	96.99%	24.91%	12.40%	65.70%	21.90%
Total	9,242	1,898	87.20%	94.41%	56.29%	6.67%	48.76%	44.57%

Panel B: time to first downgrade and downward rating revision

				Percentile		
	N	Mean	St. Dev.	25th	50th	75th
Days to first downgrade						
by Moody's	7,588	635.09	391.08	321	518	746
by S&P	6,458	575.1	358.99	299	466	886
by Fitch	3,975	513.19	354.43	258	335	761
Days to first downward rating revision						
by Moody's	7,977	554.55	319.98	311	517	706
by S&P	7,632	537.5	353.06	243	424	852
by Fitch	4,045	483.26	344.14	244	329	744

(continued)

Table I. Continued

Panel C: distribution of first rating action among rating agencies for jointly rated tranches					
	N	(A) First	(B) First	Ties	Wilcoxon *z*
First Downgrade					
(A) Moody's versus (B) S&P	7,695	62.73%	31.94%	5.33%	35.03***
(A) Moody's versus (B) Fitch	4,462	38.12%	54.82%	7.06%	10.75***
(A) S&P versus (B) Fitch	4,813	22.04%	64.01%	13.95%	28.61***
First Down. Rating revision					
(A) Moody's versus (B) S&P	7,695	63.92%	35.46%	0.62%	27.52***
(A) Moody's versus (B) Fitch	4,462	46.17%	51.73%	2.10%	2.71***
(A) S&P versus (B) Fitch	4,813	35.92%	57.49%	6.59%	13.83***

2011. *Days to first downgrade* is the number of days elapsed from June 1 2007 to the day of the first downgrade; *Days to first downward rating revision* is the number of days elapsed to the first downgrade or inclusion in a negative watchlist (whichever occurs first). Inclusion in a negative watchlist before a downgrade appears to be a more common practice for Moody's and S&P than for Fitch: around 47% and 44% of tranches downgraded by Moody's and S&P, respectively, are previously included by the CRA in a negative watchlist; for Fitch, the percentage is only 17%. When tranches are included in a negative watchlist before the downgrade, the median time elapsed between the two decisions is 154, 132, and 118 days for Moody's, S&P, and Fitch, respectively.

On average, Fitch appears to apply the faster rating revisions; its mean (median) time to first downgrade is around 4 (6) months shorter than Moody's and 2 (4) months shorter than S&P. This result is confirmed in Panel C, where statistics regarding the identity of the first downgrading agency for jointly rated tranches are reported. In 54.82% (64.01%) of the cases, Fitch downgrades tranches rated jointly with Moody's (S&P) before the rival. A Wilcoxon signed-rank test rejects the null hypothesis that the median difference in the timing of downgrades is 0 at the 1% confidence level. Percentages are somewhat lower when the days to the first downward rating revision are considered, but the median difference is still statistically different from 0% at the 1% confidence level. As for tranches rated jointly by Moody's and S&P, the former agency appears to significantly lead the rating revision process—a result consistent with those of Güttler and Wahrenburg (2007) on corporate bonds.

In unreported analysis, we examine the ratings distribution and average differences in ratings as at June 2007 for tranches rated jointly by Moody's and S&P, Moody's and Fitch, and S&P and Fitch.[7] As at June 2007, almost all (approximately 97%) of the jointly rated tranches by Moody's and S&P were considered investment grade—that is, ratings between Aaa/AAA and Baa/BBB. The proportion of tranches receiving exactly the same rating by the two CRAs is relatively high, especially among the issues rated Aa/AA and Aaa/AAA, and the average gap in ratings measured in notches (i.e., the number of rating levels in the alphanumeric scale) over the whole subsample is only 0.29. In cases of split ratings (i.e., different evaluations in the alphanumeric rating scale), S&P was clearly the agency assigning the highest rating, with less than 5% of jointly rated tranches receiving a less severe evaluation by Moody's.

However, there is quite a different picture for Moody's and S&P versus Fitch. While the average rating gap is still very small (0.1–0.3 notches) and the proportion of tranches rated more severely by Moody's (S&P) or Fitch as at June 1 2007 are substantially balanced, the proportion of tranches rated equally is clearly lower than that observed for tranches jointly rated by Moody's and S&P—only 19.56% (19.59%) against 75.04%. Thus, neither Moody's nor S&P appear to be significantly more or less severe than Fitch before the start of the crisis, but it is evident that the ratings by the two larger CRAs were more aligned with each other than those of Fitch.

3.2 CONTROL VARIABLES

For each tranche collected from Bloomberg, we consider a number of characteristics likely to affect the phenomena under study. Descriptive statistics for our set of variables are reported in Table A.2 of the Supplementary Appendix. We use several control variables for the credit quality and credit quality deterioration of each tranche. *Credit support* measures a tranche's overcollateralization expressed as a percentage relative to the tranche notional amount. The variable is measured with a monthly frequency on the first day of each calendar month. In this way, we can control for the effective evolution over time of credit quality on the timing of rating revisions. The level of credit support has substantially decreased in the aftermath of the crisis: the median (mean) support falls by around 660 (312) basis points between June 2007 and July 2011.

We also include other controls found in previous research to better predict credit deterioration in the aftermath of the crisis. *FICO Score* is the mean value-weighted FICO score (an indicator of borrowers' credit worthiness)

[7] Details are suppressed to conserve space, but interested readers can see the Supplementary Appendix—Table A.1.

associated with underlying loans. As expected for HEL securities, both mean and median values of *FICO Score* are well below the US median value of 720.[8] *Amount* is the tranche notional amount in USD millions. As deals are typically structured in one large Senior tranche and several smaller Mezzanine and Subordinated tranches (He, Qian, and Strahan, 2012), the distribution of this variable is positively skewed, with a mean value of 61.57 USD million and a median value of 21.85 USD million. As a further control for the credit worthiness of borrowers, we also include the value-weighted average of the annual interest rate paid on loans (*WAI*). Finally, as a proxy for the level of diversification in the collateral, we consider the number of loans backing the deal (*No. of loans*).

In our analyses, we also use several indicators to control for the structure of the deal and the tranche typology. Mezzanine and Subordinated are two indicator variables equal to 1 if the tranche is a mezzanine (subordinated to senior tranches) or a subordinated (lowest seniority) issue, respectively, and 0 otherwise. Pass-through is a dummy equal to 1 if tranche payments are based on actual or scheduled payments on the underlying mortgage portfolio, and 0 otherwise. (*Non*) *Accelerated Security* is a dummy equal to 1 if the tranche receives payments faster (slower) than its collateral, and 0 otherwise. *Sequential* is a dummy equal to 1 if the tranche starts paying principal only when other tranches have paid it fully, and 0 otherwise. Finally, *Principal Only* (*Interest Only*) is a dummy variable equal to 1 if the tranche only pays out from principal (interest) repayments on the collateral, and 0 otherwise.

4. Empirical Results

4.1 IMPACT OF DOWNGRADES

To begin, we assess how downgrades by rivals affect the timing of downgrades of each CRA. Following Güttler (2011) and Mählmann (2011), we study the timing of rating revisions by estimating Cox proportional hazard models. Time is measured as the number of elapsed days since June 1 2007 to the occurrence of the first downgrade by each agency. Each model is estimated using tranches effectively rated and downgraded by the CRA of interest in the period under study; every tranche exits the analysis at the first occurrence of a downgrade by the analyzed CRA. To account for the fact that securities by the same issuer are typically downgraded together

[8] “Report to the Congress on Credit Scoring and its Effects on the Availability and Affordability of Credit.” Board of Governors of the Federal Reserve System, August 2007.

(Mählmann, 2011), as well as to control for potential unobservable characteristics of the issuer that might influence the downgrade intensity, we consider the within-issuer correlation as the result of a gamma-distributed latent issuer-level effect.[9]

For each CRA, we estimate three models: two accounting separately for the presence of a downgrade by each rival and the other considering the rating actions of both rivals. To do so, similar to Güttler (2011), we use time-varying dummy variables (*Downgraded by Moody's*, *S&P,* and *Fitch*) equal to 1 from the day the given rival CRA downgrades the tranche for the first time, and 0 otherwise. Articulating back to our empirical predictions, in the context of this modeling setup, P1 predicts that an increase in the intensity of downgrades by Moody's and S&P associated with a Fitch rating downgrade ("Fitch-induced hazard increase"), as captured by the rating downgrade dummy variable, will be smaller than the counterpart increase in downgrade intensity associated with a downgrade by the main rival CRA.[10]

To control for the effect of credit quality, credit deterioration and tranche and structure characteristics, we include all the control variables discussed in Section 3.2. Since continuous variables are missing for several tranches, and to avoid our sample shrinking excessively, we follow Ashcraft, Goldsmith-Pinkham, and Vickery (2010) and assign a value of 0 for missing values—controlling for this by using an indicator equal to 1 for each missing continuous variable, and 0 otherwise (Unknown). We also include indicator variables for the tranche year of issuance (Vintage) and for the rating assigned on June 2007 by the analyzed CRA using the seven-level alphabetic scale: Aaa, Aa, A, Baa, Ba, B, and Caa-below (Rating). Finally, to control for the effective number of CRAs rating the tranche, we include two dummy variables, *Two CRAs* and *Three CRAs*, equal to 1 if the tranche is rated by two and three agencies, respectively, and 0 otherwise. Tranches rated by fewer agencies are more likely to have been the object of rating shopping; those securities are thus, *ceteris paribus*, more likely to have been assigned inflated ratings at issuance (Skreta and Veldkamp, 2009). As such, this might force a faster rating revision once the crisis unfolds.

Table II reports coefficient estimates for the models described above. Consistent with prediction P1, our main finding is that the downgrade hazard of both Moody's and S&P is significantly more affected by a

[9] This is called a shared frailty model and is equivalent to a random effects model in duration analysis.

[10] We summarize this articulation in Panel A of Table A.3 in the Supplementary Appendix. All ensuing analyses are covered by the remaining panels of Table A.3.

Table II. The effect of downgrades by rival CRAs on the time taken to first downgrade

This table reports the results of modeling the ratings downgrade hazard for each of the three credit ratings agencies: Moody's, S&P, and Fitch. The coefficients for various Cox proportional hazard models are estimated, including a gamma-distributed frailty at the issuer level to account for unobserved within-issuer correlation in the risk of downgrade. The dependent variable is the time (measured in days) to the first downgrade from June 1 2007 by Moody's (Models (1)–(3)); S&P (Models (4)–(6)); and Fitch (Models (7)–(9)). *Downgraded by Moody's* (*S&P, Fitch*) are dummy variables equal to 1 from the day Moody's (S&P, Fitch) downgrades a tranche for the first time, and 0 otherwise. *Credit Support* is the level of collateral support over the notional in percentage points, measured with monthly frequency as on the first day of each calendar month. For Models (3), (6), and (9), *p-value rival (A) vs. (B)* is the *p*-value for a *t*-test on the coefficients of *Downgraded by* for the two rival CRAs being equal. $ln(1+Amount)$ and $ln(1+n^{\circ}\ of\ loans)$ are the natural logarithm of 1 + Amount in USD million and 1 + the number of loans in the collateral pool, respectively. Vintage indicators are created on each tranche year of issuance. Rating indicators are on the rating assigned by given CRA in June 2007, measured using seven classes for the alphabetic scale: Aaa, Aa, A, Baa, Ba, B, and Caa-below. Unknown indicators are dummy variables equal to 1 if each of the continuous control variables is unknown, and 0 otherwise. All other variables are as defined in the main text. All models use structure, vintage, ratings and unknown indicators. Standard errors are reported in round brackets. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Moody's			S&P			Fitch		
Downgraded by									
Moody's	–	–	–	0.863***	–	0.898***	0.526***	–	0.463***
				(0.034)		(0.034)	(0.047)		(0.047)
S&P	0.889***	–	0.879***	–	–	–	–	0.575***	0.497***
	(0.030)		(0.030)					(0.052)	(0.053)
Fitch	–	0.235***	0.189***	–	0.412***	0.520***	–	–	–
		(0.035)	(0.036)		(0.037)	(0.039)			
p-value rival (A) vs. (B)			[0.000]			[0.000]			[0.651]
Two CRAs	–0.180	0.019	–0.176	–0.349***	–0.159	–0.380***	–0.285*	–0.312**	–0.342**

(continued)

Table II. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Moody's			S&P			Fitch		
	(0.153)	(0.156)	(0.153)	(0.101)	(0.100)	(0.101)	(0.149)	(0.149)	(0.149)
Three CRAs	−0.350**	−0.292*	−0.432***	−0.565***	−0.463***	−0.824***	−0.209	−0.174	−0.299*
	(0.154)	(0.158)	(0.155)	(0.105)	(0.106)	(0.108)	(0.155)	(0.155)	(0.155)
Credit Support	−0.022***	−0.026***	−0.021***	−0.027***	−0.028***	−0.025***	−0.037***	−0.036***	−0.034***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FICO Score	−0.001*	−0.002***	−0.001*	−0.001	0.000	−0.000	0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(1 + Amount)	0.012	−0.001	0.011	0.024	0.040**	0.032*	−0.079***	−0.073***	−0.068***
	(0.016)	(0.016)	(0.016)	(0.019)	(0.019)	(0.019)	(0.024)	(0.024)	(0.024)
ln(1 + n° of loans)	−0.063***	−0.036*	−0.064***	0.080***	0.077***	0.074***	−0.018	−0.018	−0.014
	(0.020)	(0.021)	(0.020)	(0.024)	(0.024)	(0.024)	(0.032)	(0.032)	(0.032)
WAI	0.057***	0.075***	0.059***	0.074***	0.050***	0.071***	0.017	0.005	0.004
	(0.015)	(0.015)	(0.015)	(0.017)	(0.017)	(0.016)	(0.026)	(0.026)	(0.026)
Frailty variance	0.526***	0.661***	0.508***	0.331***	0.380***	0.293***	0.948***	0.944***	0.919***
	(0.079)	(0.097)	(0.078)	(0.049)	(0.055)	(0.045)	(0.155)	(0.157)	(0.152)
No. of observations	178,657	178,657	178,657	142,465	142,465	142,465	64,658	64,658	64,658
No. of tranches	7,588	7,588	7,588	6,458	6,458	6,458	3,975	3,975	3,975
No. of issuers	138	138	138	165	165	165	114	114	114

downgrade of the other main rival than by the presence of a downgrade by Fitch. Looking at Model (3) estimates, we see that, other things equal, the downgrade hazard for Moody's is increased by around 141% (i.e., exp(0.879) = 240.85%) in the case of a downgrade by S&P, but only by 21% in the case of a downgrade by Fitch. The difference, 120%, is economically remarkable and statistically significant at the 1% confidence level. Similarly, Model (6) estimates show that the downgrade hazard for S&P increases by 145% when Moody's downgrades the security, but only by 68% in the case of a downgrade by Fitch. The difference (77%) is smaller than for Moody's, but still economically sizable and statistically significant at the 1% confidence level. In contrast, Model (9) estimates suggest that Fitch is equally influenced by the rating revision of Moody's and S&P; its downgrade hazard is increased by 59% and 65%, respectively, with the difference being statistically insignificant at customary confidence levels.

Comparing the reciprocal effect of each CRA on each other, we also see that, consistent with P3, Moody's rating actions appear to influence Fitch's more than the other way around. Depending on the model, Moody's downgrades increase the hazard rates for Fitch between 59% and 69%, whereas the effect of downgrades by Fitch on Moody's is estimated to be between 21% and 26%. When considering the reciprocal effects of S&P versus Fitch, the difference is somewhat less clear: S&P downgrades increase the hazard rate for Fitch by between 64% and 77%, while Fitch downgrades increase S&P's hazard rate by 51–68%. Finally, Moody's and S&P appear to have a very similar influence on each other: downgrades by either increase the downgrade of the other by about 140%.

In sum, we find that the smaller agency (Fitch) is more influenced by, than influential on, the behavior of the two main CRAs, who appear to imitate more promptly each others' decisions rather than those of the smaller rival. These results are highly consistent with the role of reputation on herding behavior that the theoretical literature suggests. Our results largely conform to predictions P1 and P3.

Before moving to our next analysis, it is worth commenting briefly on the sign of estimated coefficients for the control variables. First, as expected, lower credit support is associated with a downgrade hazard significantly higher (at the 1% confidence level) in all models. Second, the presence of multiple CRAs, as captured by the dummies, *Two CRAs* and *Three CRAs*, generally result in lower hazard rates—a finding consistent with rating shopping concerns. Tranches backed by loans associated with higher interest rates experience on average faster downgrades, while for other continuous control variables, the empirical evidence is mixed. Finally, the frailty variance is statistically significant at the 1% confidence level in all models, which confirms the importance of controlling for potential effects at the issuer level.

4.2 IMPACT OF DOWNWARD RATING REVISIONS

Downgrades are not the only negative rating actions that CRAs can undertake—agencies can decide to place a security on a negative watchlist for future downgrades. Hamilton and Cantor (2004) show that securities included in a negative watchlist by Moody's have almost 70% probability of being downgraded within the subsequent 3 years. Moreover, they find that the accuracy of default frequency predictions is significantly improved when securities included in a negative watchlist are treated as nonwatchlisted securities with a two-notch lower rating. Norden and Weber (2004) provide empirical evidence that negative watchlist inclusions for corporate bonds are associated with larger abnormal performance of their CDSs and shares than subsequent downgrades. In sum, previous research suggests that inclusions in a negative watchlist can, to some extent, be considered as downgrades and can constitute a timelier signal to the market, and thus to rival CRAs as well.

To incorporate a negative watchlist effect in our analyses, we reestimate models presented in Table II by substituting the three time-varying dummies *Downgraded by* with dummies equal to 1 from the day a particular rival CRA performs its first downward rating revision—either a downgrade or a negative watchlist inclusion—and 0 otherwise (*Down. rating revision by*). Results are presented in Table III. For the sake of brevity, we do not report estimated coefficients for control variables; their sign and statistical significance are generally aligned to those observed in Table II.

Once again, we find that Moody's and S&P are more influenced by each other's rating revisions than by Fitch's. Looking at Model (3) estimates, the downgrade hazard for Moody's in the case of a downward rating revision by S&P is 128% higher than in case of a downward rating revision by Fitch. Similarly, Model (6) estimates show a 100% higher increase in the downgrade hazard for S&P corresponding to rating revisions by Moody's, compared to rating revisions by Fitch. Both differences are statistically significant at the 1% confidence level. Hence, empirical prediction P1 is supported.

Differences in reciprocal influences appear even clearer than in Table II. Moody's rating revision increases the hazard of Fitch's by 76–94%, while the effect of rating revisions by Fitch increase Moody's downgrade intensity by only 21–28%. S&P rating revisions increase the downgrade hazard for Fitch by 84–103%, while the effect of Fitch rating revisions on the downgrade intensity of S&P is estimated to be between 45% and 64%. Similar to

Table III. The effect of downward rating revision by rival CRAs on the time taken to first downgrade

This table reports the results of modeling the rating revision hazard for each of the three credit ratings agencies: Moody's, S&P, and Fitch. The coefficients for various Cox proportional hazard models are estimated, including a gamma-distributed frailty at issuer level to account for unobserved within-issuer correlation. Time as risk is measured as the number of days to the first downgrade from June 1 2007 by the considered agency. *Down. Rating revision by Moody's* (*S&P, Fitch*) are dummy variables equal to 1 from the day Moody's (S&P, Fitch) downgrades or includes a tranche in a negative watchlist for the first time, and 0 otherwise. *No. of CRAs* is a dummy variables equal to 1 if two or three CRAs respectively rate the tranche, and is 0 otherwise. Other controls include *Credit Support, FICO score*, $ln(1+Amount)$, $ln(1+n^{\circ}\ of\ loans)$ and *WAI*. All other variables are as defined in Table II. Standard errors are reported in round brackets. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Moody's			S&P			Fitch		
Down. Rating revision by									
Moody's	–	–	–	0.940***	–	0.972***	0.662***	–	0.568***
				(0.033)		(0.033)	(0.043)		(0.044)
S&P	0.921***	–	0.911***	–	–	–	–	0.706***	0.611***
	(0.028)		(0.028)					(0.043)	(0.044)
Fitch	–	0.247***	0.190***	–	0.373***	0.496***	–	–	–
		(0.035)	(0.036)		(0.037)	(0.039)			
p-value rival (A) vs. (B)			[0.000]			[0.000]			[0.517]
No. of CRAs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Structure indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vintage indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unknown indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Frailty variance	0.425***	0.660***	0.409***	0.292***	0.383***	0.257***	0.889***	0.856***	0.806***
	(0.065)	(0.097)	(0.063)	(0.045)	(0.055)	(0.041)	(0.144)	(0.142)	(0.132)
No. of Observations	178,657	178,657	178,657	142,465	142,465	142,465	64,658	64,658	64,658
No. of tranches	7,588	7,588	7,588	6,458	6,458	6,458	3,975	3,975	3,975
No. of issuers	141	141	141	171	171	171	114	114	114

Table II, there is no significant difference on the impact of Moody's and S&P on the timing of downgrades by Fitch (*p*-value 0.52), and the reciprocal effects of Moody's on S&P and vice versa are also indistinguishable. Therefore, prediction P3 is further supported.

4.3 ROBUSTNESS CHECKS

We perform a series of additional analyses to confirm the robustness of our results. First, we include dummy variables to control for the issuer identity instead of using a shared-frailty approach. Second, we measure time at risk starting from January 1 2007 instead of June 1 2007, thus including downgrades that occur in the first 5 months of 2007 into the analyses.[11] Third, to account for the possibility that CRAs might react to rating revisions of rivals by including securities in a watchlist for further evaluation instead of directly downgrading it, we reestimate the models of Table III by also measuring time at risk as the number of elapsed days since June 1 2007 to the first downward rating revision (either negative watchlist inclusion or downgrade). Finally, to control for potential anticipation by CRAs about the disruption of credit quality, we include up to 3-month lead values for *Credit support*. Estimated coefficients regarding all of the aforementioned robustness analysis are reported in Tables A.4, A.5, and A.6 of the Supplementary Appendix. In all cases, our main results are confirmed: the influence of Moody's and S&P on each other is higher than that of Fitch, and downgrades/rating revisions by the two main CRAs (especially Moody's) appear to have a higher impact on the timing of Fitch rating revisions than vice versa.

In principle, our results might be partially driven by endogeneity, as downgrades are not random events. To the extent that CRAs receive at the same point in time some private information about credit quality (i.e., information not captured by the effective deterioration of credit quality that we can observe), this latent variable might help explain the positive correlation of rating revision activity of alternative CRAs across time. However, as noted by Güttler (2011), this latent variable cannot explain the observed relative differences in estimated coefficients across CRAs. It might be possible that these observed differences in coefficients are related to the fact that private information about credit quality is observed by different CRAs at different points in time. For example, if Moody's or S&P were to systematically observe some private information about credit quality before Fitch, the

[11] In this case, we exclude securities issued during the first 5 months of 2007 to avoid delayed entries.

higher coefficients associated with downgrades of those two agencies might simply reflect that they are able to apply faster downgrades than Fitch because of this more timely information. However, to give this alternative explanation more persuasive power, we would expect Moody's and S&P to execute, on average, rating revisions before Fitch does. As the descriptive statistics presented in Panel C of Table I show, the opposite is true: the least influential CRA (Fitch) more often produces downward rating revisions before either of its peers. Thus, the potential omitted variable is expected to induce underestimation of the difference in the influence of Moody's and S&P rating actions against those of Fitch. In sum, we argue that we have sufficient consistent elements to justify the interpretation of our main results—namely, that they are reflective of predictable differences among CRAs in their relative influence on herding by rivals.

4.4 SPLIT RATINGS AND TIME TO FIRST DOWNGRADE

Before moving to a static analysis of how split ratings have changed after the advent of the crisis, we explore further the timing of rating revisions by more closely assessing the role played by rating disagreements among CRAs. As discussed above, a meaningful proportion of jointly rated tranches exhibit split ratings as at June 2007, especially involving Fitch.[12] Herding arguments predict that CRAs assigning different ratings eventually converge toward the same evaluations. Again, our main point of interest is to assess relative differences in how timely are rating agencies in adjusting their evaluations to take into account those of their rivals. To do so, we reestimate Models (3), (6), and (9) of Table II, augmented with a dummy variable equal to 1 for each analyzed CRA if it assigns a rating higher than a rival as at June 1 2007, and 0 otherwise (*Higher rating*).

[12] It should be noted that, in theory, split ratings could merely reflect divergent meanings attributed to the same rating label by different CRAs. Doherty, Kartasheva, and Phillips (2012) show that misalignment in rating scales might occur as a result of strategic choices by CRAs. However, given the common practice by markets, regulators and academics alike to consider rating scales by the big three as comparable (e.g., Cantor and Packer, 1997) and considering the nature of the phenomena under study here, we argue that it is legitimate to consider the presence of a "nominally" split rating as a reflection of information that rival CRAs wish to embed in their evaluations for reputational purposes. Consistent with this, Moody's (2007) reports that structured finance products rated only by S&P (or Fitch) would have been characterized by stronger rating disagreements between Moody's and the other CRAs than that observed for the average security actually rated by both Moody's and its rivals.

We estimate six models, two for each CRA, taking into account split evaluations with one or the other rival. In the context of this modeling setup, P2 predicts that an increase in the downgrade intensity induced by the presence of a more severe evaluation by Fitch ("Fitch-induced hazard increase"), as captured by the higher rating dummy variable, will be smaller than the counterpart hazard increase associated with the presence of a lower rating assigned by the main rival CRAs.[13] Moreover, P3 predicts that the presence of a more severe evaluation by Moody's (S&P) will increase the downgrade intensity for Fitch more than the converse.[14] The results are reported in Table IV.

As Models (1) and (3) show, both Moody's and S&P called more timely downgrades when their main rival assigned a more severe evaluation before the crisis began. *Ceteris paribus*, Moody's downgrade hazard is increased by around 63% (significant at the 1% confidence level), while the S&P downgrade hazard is increased by 10% (significant at the 5% confidence level). Moody's thus exhibits a stronger tendency toward rating convergence with S&P than the other way around, which is consistent with Güttler (2011).

Once again, we find that the influence of the two main CRAs on each other is stronger than the influence by Fitch, and that they influence Fitch more than the other way around. As Models (2) and (4) show, the timing of downgrades by either Moody's or S&P is not significantly affected by the presence of more severe ratings by Fitch. The latter is instead estimated to increase its downgrade intensity by 32% (significant at the 1% confidence level) in the presence of a more severe rating by Moody's, and by 11% (significant at the 10% confidence level) when there is a more severe rating by S&P. Collectively, these results provide support for predictions P2 and P3.

4.5 SPLIT RATINGS AND LIKELIHOOD OF CONVERGENCE

Thus far, we have shown how rating revisions by rivals and rating disagreements significantly influence the timing of rating revisions by each CRA to varying degrees, depending on the identity of the rival. In particular, empirical evidence presented in Section 4.4 suggests that Fitch tends to apply more timely downgrades to converge toward Moody's and S&P ratings, while the opposite does not seem to hold. To provide further evidence regarding this

[13] Refer to the Supplementary Appendix, Table A.3., Panel B.
[14] Refer to the Supplementary Appendix, Table A.3, Panel C.

Table IV. The effect of split ratings on the time taken to first downgrade

This table reports the results of modeling the ratings downgrade hazard for each of the three credit ratings agencies: Moody's, S&P, and Fitch. The coefficients for Cox proportional hazard models are estimated, including a gamma-distributed frailty at the issuer level to account for unobserved within-issuer correlation. In each model, we include a dummy equal to 1 if the CRA under analysis on June 1 2007 assigned a *Higher rating* (at alphanumeric level) than the other given CRA, and 0 otherwise. Models (1) and (2) relate to Moody's time to downgrade, controlling for the presence of lower ratings by S&P and Fitch, respectively. Models (3) and (4) relate to S&P's time to downgrade, controlling for the presence of lower ratings by Moody's and Fitch, respectively. Models (5) and (6) relate to Fitch's time to downgrade, controlling for the presence of lower ratings by Moody's and S&P, respectively. All other variables are as indicated in Table II and defined in the main text. Standard errors are reported in round brackets. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	(1) versus S&P	(2) versus Fitch	(3) versus Moody's	(4) versus Fitch	(5) versus Moody's	(6) versus S&P
	Moody's		S&P		Fitch	
Higher rating	0.484***	−0.025	0.090**	−0.029	0.279***	0.102*
	(0.067)	(0.035)	(0.037)	(0.039)	(0.054)	(0.057)
Downgraded by						
Moodys	–	–	0.894***	0.896***	0.463***	0.464***
			(0.034)	(0.034)	(0.047)	(0.047)
S&P	0.872***	0.879***	–	–	0.513***	0.499***
	(0.030)	(0.030)			(0.053)	(0.053)
Fitch	0.196***	0.185***	0.527***	0.519***	–	–
	(0.036)	(0.037)	(0.039)	(0.039)		
No. of CRAs	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Structure indicators	Yes	Yes	Yes	Yes	Yes	Yes
Vintage indicators	Yes	Yes	Yes	Yes	Yes	Yes
Rating indicators	Yes	Yes	Yes	Yes	Yes	Yes
Frailty variance	0.511**	0.507***	0.293***	0.294***	0.906***	0.911***
	(0.078)	(0.077)	(0.045)	(0.045)	(0.151)	(0.151)
No. of observations	178,657	178,657	142,465	142,465	64,658	64,658
No. of tranches	7,588	7,588	6,458	6,458	3,975	3,975
No. of issuers	138	138	165	165	114	114

phenomenon, we now explore how the presence of a split rating between two CRAs before the onset of the crisis impacts the probability that, by the end of our sampling period, the two agencies in question assign the same evaluation—that is, that they converge. If Fitch is the CRA with a stronger tendency toward rating convergence, we would expect the likelihood of observing equal ratings assigned by Fitch and Moody's (or S&P) by the end of July 2011 to be higher when Fitch, rather than Moody's (or S&P), was assigning the less severe rating before the start of the crisis (i.e., P3).[15]

To operationalize our analysis, we define a new variable, *Split Post*, as a categorical variable that, for each pair of rating agencies (A) and (B) and for every tranche jointly rated by (A) and (B), identifies whether as of July 29 2011: (i) (A) assigns a higher rating; (ii) (B) assigns a higher rating; (iii) the two CRAs assign the same rating (at a given alphanumeric level). Similarly, we create three dummy variables, *Higher by (A)*, *Higher by (B)*, and *Equal*, to identify the presence of split ratings as of June 1 2007. We then estimate a multinomial logit model for each pair of CRAs to assess how the relative evaluation before the start of the crisis affects the likelihood of rating convergence. For each pair, we use all tranches jointly rated and estimate two models, one including only *Higher by (A)*, *Higher by (B)*, and *Equal* among the explanatory variables and the second also including all time-invariant control variables considered so far (for *Credit support*, we use the June 2007 value). To ease interpretation, we report the estimated marginal effect of *Higher by (A)*, *Higher by (B)*, and *Equal* on each of the possible values assumed by *Split Post* in Table V.[16] In the context of this modeling setup, P3 predicts that the marginal effect of a more favorable rating assigned by Fitch, before the advent of the crisis, on the likelihood of rating convergence with Moody's (S&P) will be stronger than the marginal effect associated with a more benign initial evaluation by Moody's (S&P).[17]

Table V shows how the presence of split evaluations between Moody's (or S&P) and Fitch affects the likelihood of rating convergence. Using estimated coefficients from Models (3) to (6), we see that the likelihood of observing the same rating assigned by Moody's (S&P) and Fitch in July 2011 is 7.7–13.3% (12.8–23.3%) higher when Fitch is the less severe agency of the two before the start of the crisis. These differences are all statistically significant at the 1% confidence level. Again, this result suggests a stronger convergence tendency by Fitch toward Moody's and S&P evaluations rather than the other way around, consistent with P3. When considering jointly rated tranches by Moody's and S&P, observing an aligned evaluation by July 2011 is equally likely regardless of which CRA rating was more severe in June 2007.

[15] Note that setting our analysis during the subprime crisis allows us to consider "convergence" as "downward convergence". In general, convergence could also be toward the higher rating of the two.

[16] For models including other control variables, marginal effects are computed assigning its sample mean value to each control variable.

[17] Refer to the Supplementary Appendix, Table A.3, Panel C.

Table V. Marginal effect of split ratings before the crisis on the likelihood of rating convergence

This table reports marginal effects of equal/split ratings (as at June 2007) on the likelihood of an equal/split rating in July 2011. Effects are computed using coefficients of a multinomial logit model estimated on jointly rated tranches only. For each pair of rating agencies (A) and (B), the dependent variable (*Split post*) is a categorical variable indicating if, as at July 2011: agency (A) assigns a higher rating (*Higher by (A)*); agency (B) assigns a higher rating (*Higher by (B)*); the two ratings are equal (*Equal*). The main explanatory variables are indicators for a rating *Equal* or *Higher by* agency (A) or (B) as at June 2007. Models (2), (4), and (6) include all variables described in Section 3.2, as well as Vintage, Unknown and Rating (using the average rating assigned by the two CRAs) indicators. For those models, marginal effects are computed by assigning sample mean values to all control variables. *(A) – (B) Higher* is the difference between the marginal effect of *Higher by (A)* and *Higher by (B)* on the likelihood of each of the possible values of *Split_post*. Standard errors are reported in round brackets. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	(A) Moody's versus (B) S&P		(A) Moody's versus (B) Fitch		(A) S&P versus (B) Fitch	
Control variables	No	Yes	No	Yes	No	Yes
N	7,695	7,695	4,462	4,462	4,813	4,813
Pseudo R^2	0.01	0.11	0.04	0.14	0.04	0.21
Panel A: Pr[Split post = Equal]						
Equal	0.215***	0.215***	0.267***	0.266***	0.269***	0.287***
	(0.005)	(0.006)	(0.015)	(0.027)	(0.014)	(0.028)
Higher by (A)	0.304***	0.211***	0.195***	0.210***	0.138***	0.136***
	(0.026)	(0.023)	(0.009)	(0.012)	(0.008)	(0.009)
Higher by (B)	0.283***	0.206***	0.328***	0.287***	0.371***	0.265***
	(0.011)	(0.011)	(0.011)	(0.015)	(0.011)	(0.015)
(A)–(B) Higher	0.021	0.005	−0.133***	−0.077***	−0.233***	−0.128***
	(0.028)	(0.024)	(0.015)	(0.021)	(0.014)	(0.017)
Panel B: Pr[Split post = Higher by (A)]						
Equal	0.068***	0.047***	0.233***	0.250***	0.505***	0.516***
	(0.003)	(0.003)	(0.014)	(0.026)	(0.016)	(0.033)
Higher by (A)	0.169***	0.136***	0.392***	0.284***	0.715***	0.731***
	(0.021)	(0.022)	(0.011)	(0.014)	(0.010)	(0.014)
Higher by (B)	0.051***	0.054***	0.124***	0.159***	0.437***	0.511***
	(0.005)	(0.007)	(0.008)	(0.011)	(0.011)	(0.017)
(A)–(B) Higher	0.119***	0.082***	0.268***	0.124***	0.277***	0.220***
	(0.022)	(0.022)	(0.014)	(0.020)	(0.015)	(0.024)
Panel C: Pr[Split post = Higher by (B)]						
Equal	0.717***	0.738***	0.501***	0.484***	0.226***	0.197***
	(0.006)	(0.007)	(0.017)	(0.030)	(0.014)	(0.023)
Higher by (A)	0.527***	0.653***	0.413***	0.506***	0.148***	0.133***
	(0.028)	(0.029)	(0.012)	(0.015)	(0.008)	(0.011)
Higher by (B)	0.666***	0.740***	0.548***	0.554***	0.192***	0.224***
	(0.012)	(0.012)	(0.012)	(0.016)	(0.009)	(0.014)
(A)–(B) Higher	−0.140***	−0.087***	−0.135***	−0.047*	−0.044***	−0.092***
	(0.030)	0.031	(0.017)	(0.025)	(0.012)	(0.019)

In Table V, we also report marginal effects on the likelihood of observing split ratings by July 2011. For all pairs of CRAs, the likelihood of observing a higher rating assigned by one particular agency is significantly higher if that agency was rating that security less severely than the other rival in June 2007. For example, the probability of having a higher rating by Moody's in July 2011 is about 10% higher if Moody's rating was also the higher of the two in June 2007. Similarly, a higher rating by S&P is 8.0–14.0% more likely if S&P, rather than Moody's, was already the less severe agency. These results suggest that, while heading toward convergence in their evaluations, CRAs do not appear to try to overcompensate more generous prior evaluations on a particular tranche by assigning lower ratings than their rivals.

5. Conclusion

In this article, we investigate relative differences in the impact of rating actions and disagreements across the three main CRAs (Moody's, S&P, and Fitch) on the timing of their rating revisions and the likelihood of rating convergence. Using a sample of US ABS Home Equity Loans issued before June 2007, we find that since the start of the subprime crisis, both Moody's and S&P applied faster downgrades in the case of a downgrade by the other main rival compared to the case of a downgrade by Fitch. Further, their rating actions (especially those of Moody's) appear to influence the downgrade intensity of Fitch more than the other way around. All three agencies apply more timely downgrades in the presence of a more severe rating by Moody's or S&P, but the downgrade intensity of these two agencies does not seem to be affected by the presence of a lower rating by Fitch. Finally, we show that the likelihood of rating convergence, 4 years into the crisis, for tranches jointly rated by Moody's (or S&P) and Fitch is higher when the smaller of the three agencies assigns the highest rating before the crisis started, while the effect of split evaluations on jointly rated tranches by Moody's and S&P does not appear to depend on the identity of the agency assigning the less severe rating. As Fitch is usually regarded as the weakest of the three CRAs, our results are consistent with the predictions from theoretical models on the role of reputation in explaining herding behavior among CRAs.

Our results are of great interest to regulators. Since the onset of the subprime crisis, there have been several mooted changes in the regulation of the credit rating industry designed to enhance reputational incentives, competition, and transparency, especially for structured finance products. Many commentators have argued that some of these reforms, such as those discussed in the Dodd–Frank Act, might increase the conformity bias among CRAs evaluations (e.g., Manns, 2013). Our study documents the extent and relative differences of herding behavior among CRAs that are already in place.

The strength of incentives toward herding appears to vary with the reputational capital of the CRAs involved. In this sense, proposed reforms trying to facilitate competition among smaller CRAs, such as the European Parliament's proposal that issuers should appoint at least one CRA with a market share lower than 10%, might have nontrivial effects on the level of rating independence, especially if the smaller agency takes the place of another bigger CRA that would have otherwise rated the issue. On the one hand, rating actions by the main CRAs evaluating the security might be more independent on securities jointly rated with smaller rivals. On the other hand, our results suggest that the latter might have strong incentives to herd toward the rating evaluations given by the rival with a higher reputation. Accordingly, future research should extend upon our analysis and consider CRAs other than the "big three" to empirically assess the herding tendency of these smaller CRAs and their level of influence over the decisions made by the main agencies.

Supplementary Material

Supplementary data can be found at *Review of Finance* online.

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