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Abstract

We assess herding by considering the lead-lag relationship of sovereign ratings assigned by the 3 main rating agencies at the individual country level. The only previous study of such a lead-lag relationship (Alsakka and ap Gwilym, 2010) used pooled data methods that assume this lead-lag relationship is homogeneous across countries. Given that different rating agencies may have different levels of expertise (reputation) for different countries it is not obvious that such homogeneity holds. We therefore conduct poolability tests within this context to assess this assumption and find evidence of heterogeneity. This leads us to conduct country-by-country time-series tests to assess the lead-lag relationship among agencies. To our knowledge we are the first to do this and thereby extend the literature on herding among rating agencies' sovereign assignments. We also consider changes in the lead-lag relationship through time by splitting the sample into pre-crisis and crisis periods to assess the extent to which any herding is intentional and our results indicate some degree of heterogeneity through time. To the extent that there is herding we find that it is generally towards Standard and Poor's ratings confirming our expectations given that this agency is regarded as possessing the greatest reputational capital. However, our results do not support the expectation that Fitch is a follower for more (a leader for less) countries than Moody's.

Keywords: sovereign ratings, herding, cross-country heterogeneity
JEL classification: C25, C52, G24

1. Introduction

The reputation of Credit Rating Agencies (CRAs) was tarnished during the Global Financial Crisis (GFC) in 2007/2008. Since the GFC it has become evident that CRAs systematically mispriced risk through inflated rating assignments. Empirical and theoretical studies have, for a long time, challenged the role of CRAs within financial markets. In particular, the policies of rating assignments conducted by the largest CRAs that include Moody's, Standard and Poor's (S&P's hereafter) and Fitch Ratings have been questioned. None of these CRAs provided any warning signals about the problems before the GFC. This became evident when financial markets faced a full-blown crisis. At the outset of the GFC an unprecedented number of the rated entities and financial instruments issued by financial institutions, governments and corporates suffered from multi-notch downgrades. These massive downgrades show that ratings assigned by CRAs failed to reflect the true risk of the rated entities.[1] As a result, the unique position of CRAs within the financial market has been even more scrutinised and criticised by governments and regulators.

The signs of inflated ratings were observable even before the GFC, e.g., Enron and Worldcom. Liberman (2002), for example, argues that the largest CRAs over the last 30 years gained quasi-governmental power to determine which companies within the corporate world are creditworthy and which are not. White (2010) discusses how Moody's and S&P's received a special status as "nationally recognised statistical rating organization[s]" in 1975. That meant that CRAs gained power, for example, to affect an issuer's cost of raising capital (banks use credit ratings for calculating their capital requirements).

Recent papers on CRAs attempt to explain the causes of inflated ratings information bias through CRAs reputation, competition, ratings shopping, and conflict of interest between CRAs and financial institutions, see, for example, Skreta and Veldkamp (2009), Becker and Milbourn (2011), Bar-Isaac and Shapiro (2011), Bolton, Freixas and Shapiro (2012), and Goel and Thakor (2015) among others.

A frequent argument of these studies is that the market structure in which CRAs operate could contribute to the biased and inflated ratings. The market structure may affect decision-

[1] Benmelech and Dlugosz (2009) report that 64% of all downgrades in 2007 and 2008 were linked to home equity loans or first mortgages as collateral. Collateralized debt obligations (CDOs) backed by asset-backed securities (ABS) accounted for a large share of the downgrades and some of the most severe downgrades.

taking independence in ratings assignments of individual CRAs. Moody's, S&P's and Fitch Ratings undertake their business activities in an oligopolistic market and their activities account for more than 90% of the market (OECD, 2010). Morgan (2002) argues that CRAs operate in a market environment that has prevailing oligopolistic characteristics along with an opaque process of ratings assignments. Mathis, McAndrews, and Rochet (2009), Opp, Opp and Harris (2013) and Bar-Isaac and Shapiro (2013) show that the members of a tight, protected oligopoly might become complacent and less concerned about the problems of protecting their long-run reputations.

In this paper, we further develop and extend the discussion of how a market environment can affect sovereign rating assignments. We focus on sovereign ratings in 35 countries that were assigned by Moody's, S&P's and Fitch Ratings. All three CRAs state in their reports that their sovereign rating methodologies rely on the rigorous quantitative data analyses along with qualitative evaluation. Following Cantor and Packer (1996) we assume that key determinants of sovereign rating assignments are underpinned by standard macroeconomic variables. That means that sovereign ratings should be quite similar across agencies.

We examine whether there is herding behaviour among the three largest CRAs that operate in a peculiar oligopolistic market structure (as previous research indicates). In particular, we extend current empirical research on credit ratings quality by considering heterogeneous herding behaviour of CRAs' assignments across countries. CRAs could provide the same ratings for a country independently because they base decisions on the same information. However, while different agencies produce similar ratings they are not completely the same (as is evident by casual inspection of comparative ratings). Guttler and Wahrenburg (2007), Alsakka and ap Gwilym (2010) and Lugo, Croce and Faff (2014) explore potential behavioural pattern, the timing of rating revisions, and reputational factors that may affect rating assignments due to herding. In our study, we assess herding by considering the lead-lag relationship of sovereign ratings assigned by the three largest rating agencies at the individual country level. If we find the presence of herding for at least some countries this contributes to a discussion on inflated credit rating assignments. We do not argue that there is necessarily explicit collusive behaviour among CRAs in terms of assigned ratings. What we intend to do is to examine whether changes in rating assignments across CRAs reflect rating changes by a leading rating agency.

The intuition behind this argument is that smaller and newer CRAs, eg. Fitch Ratings, that do not have the same degree of reputation as established CRAs (S&P's and Moody's), may follow assigned ratings from the reputable CRAs. Alternatively, we can argue that those CRAs that do not have the same quality of analysts and experience follow the leader in this segment of ratings – the different level of expertise across CRAs is discussed by White (2010) and Bar-Isaac and Shapiro (2011). If this is the case then inflated or incorrect ratings assessments will not be questioned since they are in line with reputable CRAs. Furthermore, CRAs may intentionally inflate or level rating assignments with their competitors to maintain (attract) potential customers due to ratings shopping (Skreta and Veldkamp, 2009; Bolton, Freixas and Shapiro, 2012). If we trace a pattern of herding among CRAs, we may also explain why there are marginal differences in the rated entities, that is, why CRAs inflate ratings in the same way.

The concept of herding behaviour across CRAs may be explained in a similar way as price leadership theory of oligopoly pricing. Alternatively, we could see the parallel with institutional industry herding. Sias (2004) and Choi and Sias (2009) provide an extensive analysis of herding behaviour among institutional investors. Sias (2004) shows that institutions herd as a result of inferring information from each other's trades. The contemporary research and empirical evidence from CRAs support the direction of this type of research, see, for example, Lugo, Croce and Faff (2014) and Alsakka and ap Gwilym (2010). The notion underlying herding behaviour is that the action of one agent is influenced by that of other agents. Within the context of sovereign ratings, herding could be interpreted as one CRA's sovereign ratings being influenced by another, even though the agencies should produce independent ratings.[2]

Our paper contributes to related literature in several ways. First, the analysis of CRAs' herding contributes to the work of recent studies by Lugo, Croce and Faff (2014) and Alsakka

[2] Alsakka *et al* (2014) suggest two channels through which banking risk can affect sovereign risk. First, the cost of bailing out banks can erode public resources and increase a nation's vulnerability to default on its debts. Secondly, weakened banks will be less able to support economic growth through their role as a financial intermediary. While they find little evidence that sovereign rating assignments influence bank rating assignments in the pre-crisis period they do find that the former strongly affect the latter during the crisis period. It is also noted that sovereign ratings no longer provide a strict ceiling to bank ratings although the former are typically higher than the latter. They also find that the link between sovereign and bank ratings vary significantly across the three CRAs. While they do not provide evidence for individual countries (because they employ a pooled probit estimation method for the 21 European countries in their sample) they do find that sovereign ratings have a greater influence on bank ratings for PIIGS (Portugal, Italy, Ireland, Greece and Spain) countries than other European countries. This is established by estimating a separate pooled model for these countries. Our method that relies on time-series regressions will facilitate a comparison in CRAs herding behaviour for sovereign ratings by each individual country, which is a strength of our work.

and ap Gwilym (2010). We provide an additional dimension to the ongoing discussion about the inflated ratings and reputation factors. Second, we contribute to recent studies investigation of institutional herding among CRAs by introducing full country heterogeneity. We extend the literature on herding among rating agencies' sovereign assignments by conducting country-by-country time-series tests to assess the lead-lag relationship among agencies and, to our knowledge, we are the first to do this. Alsakka and ap Gwilym (2010) assume that the lead-lag relationship is homogenous across countries. We argue that different rating agencies may have different levels of expertise (reputation) for different countries and it is not obvious that such homogeneity holds. We therefore conduct poolability tests to assess this assumption and find evidence of heterogeneity. Third, we consider the extent to which any apparent herding is intentional by assessing changes in herding behaviour between the pre-crisis and crisis periods.

The rest of the paper is organized as follows. Section 2 presents the related literature on credit rating assignments and identifies the gaps in the literature that directs our research hypotheses. Section 3 discusses the data and Section 4 outlines the methods used for testing our hypotheses. Section 5 presents and discusses our empirical results. Finally, Section 6 concludes, shows policy relevance of this case study and outlines a direction for further research.

2. Related Existing Literature and Building Hypotheses

Empirical and theoretical research on CRAs and ratings assignments dates back to the late 1980s. Ramakrishnan and Thakor (1984), Millon and Thakor (1985) and Cantor and Packer (1997) indirectly provide the theoretical foundation and intellectual trajectory for research that is underpinned by the theory of financial intermediation, see Leland and Pyle (1977), Allen (1990), Pagano and Jappelli (1993) among others.

A frequently cited argument underpinned by empirical research is that CRAs do not assess risk better than market participants themselves. CRAs do not have, and cannot have, superior information to market participants about uncertainty and the degree of insolvency (illiquidity) of the rated firms (sovereigns). Altman and Saunders (2001) show that CRAs may provide biased opinions since their ratings strategies are based on backward looking analyses rather than being forward looking. Amato and Furfine (2004) analyse changes of credit ratings assignments over business cycles to test the hypothesis about procyclical behaviour of CRAs.

They show that the opaque methodologies used by CRAs are conducted on a "through-the-cycle" basis, and not according to transitory fluctuations in credit quality. Bolton, Freixas and Shapiro (2009, 2012) explore a further interesting research question regarding the conflict of interest of CRAs that is linked with economic fundamentals. CRAs overestimate ratings in good times (booms) when there are a large number of naive investors and the probability of losing their reputation is lower. Their results correspond with the situation that occurred during the GFC when a large number of issued ratings were downgraded. This particular issue is further extended by Bar-Isaac and Shapiro (2013) who link endogenous reputation and the variable market environment. They find that ratings quality is countercyclical. Ammer and Packer (2000) indicate that there is rating inconsistency for US financial firms. Cantor et al. (2001) reveals that the speculative grade of US banks has higher annual default rates than US non-banks. Morgan (2002) demonstrates that the difference in two separate CRAs' bank rating assignments is explained by the inherently opaque nature of banks for those outside banks, including CRAs. Bannier, Behr and Gütler (2010) attempt to explain why unsolicited ratings tend to be lower than solicited ratings. Fulghieri, Strobl and Xia (2015) develop a dynamic rational expectations model that examines the incentive for CRAs to assign unsolicited credit ratings.

Another strand of the recent literature addresses further important research and policy related questions that are linked to reputational effects, competition and the reliability of CRAs' ratings assignments – see Becker and Milbourn (2011), Mariano (2012), Bolton, Freixas and Shapiro (2012), Manso (2013) and Bar-Isaac and Shapiro (2013). Alsakka, ap Gwilym and Vu (2014) attempt to provide a theoretical framework that explains why CRAs fail to make reliable rating assignments in terms of their timeliness and accuracy. Cantor et al (2000), Morgan (2002) and Becker and Milbourn (2011) challenge the reliability of ratings assignments with respect to their opaqueness and the degree of competition. Becker and Milbourn (2011) show that the competition among the three largest CRAs – Moody's, S&P's and Fitch Ratings – could cause the failure of adequate rating assignments.

The above studies relates to research on information bias of rating assignments that is based on decision model theory. Following Banerjee (1994) this kind of explanation is based on the assumption that each decision maker considers the decisions taken by other decision makers in taking their own decision. Such a strategy leads to herding behaviour when individual agents copy what others do instead of using their own information and judgment. The literature on herding behaviour is well established and extensive in the area of finance (Trueman, 1994, Wermers, 1999, Sias, 2004, Choi and Sias, 2009). Sias (2004) confirms the hypothesis about institutional herding. Thus, institutional investors follow each other when they buy or sell the same shares. However, they show that substantial differences exist across institutions although institutional investors follow similarly classified institutional investors.

The majority of the literature on herding focuses on fund managers investing in stocks where there are a large number of investors and stocks. When investigating herding for CRAs there are primarily 3 agencies to consider. Hence, theoretical models of pricing strategy under oligopoly provide many relevant insights into the situation of a small number of CRAs making rating assignments (which is analogous to a small number of large firms deciding how to set prices). As we discussed, the notion underlying herding behaviour is that the action of one agent is influenced by that of other agents (Scharfestein and Stein, 1990, Benerjee, 1992, Choi and Sias, 2009). Within the context of sovereign rating agencies herding could be interpreted as one CRA's sovereign ratings being influenced by another, even though the agencies should produce independent ratings.[3] The concept of herding behaviour in the context of institutional investors can be transformed into the decision process of ratings assignments. There are a few recent studies that attempt to apply it to rating assignments, e.g. Guttler and Wahrenburg (2007), Alsakka and ap Gwilym (2010) and Lugo, Croce and Faff (2014).

Given that there are three main rating agencies (Fitch, Moody's and S&P's) the notion of herding could be regarded as analogous to the microeconomic price leadership theory of oligopoly pricing. In this model firms do not explicitly collude in setting prices, however, a leading firm changes prices and the other firms follow by changing their prices in line with the leader. A modification of this theory allows for the price leader to change (possibly frequently) through time such that when any one firm changes its price the others follow.

Applying the price leadership theory to the three sovereign CRAs and considering the possibility of intentional and spurious herding more generally raises the question of whether one agency systematically leads in the setting (and changing) of country ratings. This suggests a range of hypotheses that include the following:

[3] In principle CRAs could provide the same ratings for a country independently because they base decisions on the same information. However, while different agencies produce similar ratings they are not completely the same (as is evident by casual inspection of comparative ratings).

Hypothesis 1: One CRA leads the others in changing ratings at all times and for all countries. This suggests that the follower CRA's assignments are herding towards the leader's ratings for all countries during all time periods.

Hypothesis 2: One CRA leads the others in changing ratings at all times for a particular country or countries. This suggests that the follower CRA's assignments are herding towards the leader's ratings for some countries during all time periods.

In this case, one CRA may develop, or be perceived as having developed, superior expertise in setting the rating for specific countries (perhaps based upon past performance). If the other agencies recognise this they may be inclined to follow the leader's changes in ratings - this would be intentional herding. Under this hypothesis one CRA may be viewed as the leader for one country while another may be considered the leader for another country. It may also be that there is no single recognised leader for some countries. This hypothesis would give rise to heterogeneity of leadership across countries. These hypotheses reflect current knowledge about the quality of rating analysts (Bar-Issac and Shapiro, 2011; White 2010).

Hypothesis 3: One CRA leads the others in changing ratings at different times for particular countries. This suggests that the follower CRA's assignments are herding towards the leader's ratings for at least some countries during particular time periods.

In this case, while there is no one recognised dominant agency the actions of one agency changing its rating causes other agencies to reconsider their corresponding rating such that they are likely to also change their rating.[4] This hypothesis would give rise to heterogeneity of leadership through time (possibly for a particular set of countries). If the degree of herding changes when the environment changes (as occurred after the GFC) this could indicate that herding is intentional. If the change in herding (leadership) occurs when there is no clear change in the environmental state this would suggest that herding is spurious.

Gavriilidis *et al* (2013) identify motives for traders, that we suggest can also be applied to CRAs, to *intentionally* herd as well as suggesting that herding can be *unintentional* (spurious herding). They suggest two incentives for an investor to herd *intentionally* as follows. First, the

[4] Alsakka *et al* (2014) suggest that in terms of bank ratings assignments over the GFC period S&P's tend to be the most independent while Moody's has the greatest likelihood of assigning multiple notch downgrades. Indeed, they indicate that CRAs exhibit clear differences in when and whether to alter both bank and sovereign rating assignments. This suggests that there may not be herding during the crisis. Having said this, the independence of different CRAs' *bank* rating assignments is evident only in the pre-crisis period. They find strong links between the CRAs's assignments during the crisis period. They find that S&P's are most likely to be the first to change *bank* ratings (suggesting that this CRA is concerned with reputational credibility).

investor has a view of their position relative to that of their peers and those who believe they are less able to make appropriate decisions may seek to imitate the decisions (trades) of those viewed as more able. Second, an investor may see a positive externality from following another investor's behaviour. For example, fund managers may reap "informational payoffs" by following the behaviour of managers who they believe are better informed (there are real or presumed informational asymmetries). Indeed, herding may yield "reputational payoffs" when managers (CRAs) are being judged relatively. An investor/manager (CRA) that lacks confidence in their ability may seek to mimick their peers who are deemed superior and hence conceal their (believed) inferiority. For CRAs any lack of confidence may not necessarily be for all rating assignments rather it may be for certain countries or during particular time periods or for certain countries at a particular period in time.

The appearance of herding that is spurious may arise if factors common to managers (CRAs) cause correlations in their trades (ratings assignments). For fund managers this could be the case if they are *relatively homogeneous* in terms of education, experience, information processing skills, the signals received and the regulatory environment they operate in. CRAs that work in teams (where any inadequacies of any team members can be compensated by other members) may also exhibit similar homogeneity. Hence, trades (rating assignments) may be correlated among managers (CRAs) contemporaneously or possibly with a (short) time lag with similar decisions being made independently.

Analyses attempting to distinguish intentional and spurious herding of fund managers have previously considered differences in the degree of herding for environmental states measured using market returns, market/sector volatility, market/sector trading volume and regulatory changes. For CRAs an obvious change in environment occurred after the GFC that first affected the solvency of banks and then the solvency of nations – which is the focus of our research.[5] Hence, a CRA that felt less able to make appropriate assignments for some, or all, countries may feel a greater need to conceal their (believed) lower ability during the crisis period

[5] Alsakka *et al* (2014) argue that ratings quality may be related to the business cycle. In the boom years (prior to the crisis) CRAs may not be overly concerned about ratings accuracy and that this may have caused ratings to be inflated prior to 2010. However, during the GFC (when they are subject to greater scrutiny) more effort may have been aimed at ensuring rating accuracy so causing a change in how assignments are made. If ratings were inflated prior to the crisis this could mean substantial downgrading during the crisis. Indeed, Alsakka *et al* (2014) investigate whether CRAs *bank* ratings policy changed from 2008 – 2013 compared with the pre-2008 period. Alsakka *et al* (2014) also suggest that regulatory changes were made to address shortcomings in how CRAs produced ratings prior to the GFC. Such changes may cause changes in how CRAs make assignments pre-crisis and during the crisis.

when CRAs, and their assignments, were subject to increased scrutiny due to accusations that their inaccurate (and perhaps opaque) ratings were partly to blame for the GFC.[6] Under such conditions one might expect an increased degree of intentional herding during the GFC.[7] In contrast, if CRAs do not feel inferior to others they have no incentive to herd and so any herding that appears to be evident should not change because it is unintentional. Following Lugo *et al* (2014) we expect that to the extent there is intentional herding S&P's is the most likely agency to be the leader and Fitch the most likely follower due to the relative amounts of the CRAs' reputational capital.

3. Data Sample

We estimate our models using start of period monthly data on sovereign ratings for Moody's, S&P's and Fitch Ratings in pairs.[8] Ratings are measured on a 20 point ordinal scale following the literature – see, for example, Alsaka and ap Gwilym (2010). Thus, the highest rating (AAA) is represented by 20, the second highest rating (AA+ or AA1) is 19, the rating Caa3/CCC– = 2, with all lower ratings (Ca/CC, C/C, LD/RD, D/DDD, DD, D) being set to 1 (the lowest rating category) because they are not comparable across CRAs.

Results could be obtained for 24 countries for the Fitch and Moody's CRA pairing, 28 countries for the Fitch and S&P's pairing and 23 countries for the Moody's and S&P's pairing. The sovereign ratings from Fitch Ratings and S&P's are publicly available.[9] We obtained the

[6] Alsakka *et al* (2014) suggest that the GFC has challenged the previously held belief that developed countries' sovereign debts are relatively safe – especially in countries such as Portugal, Italy, Ireland, Greece and Spain (PIIGS). They further suggest that this crisis period placed unique pressures on CRAs in terms of sovereign credit rating assignment downgrades. Given that bond yields and CDS prices would publically indicate the market's sentiment of a country's risk a CRA that appeared to act too slowly in downgrading a rating may lose credibility. Conversely, if a CRA downgrades a sovereign's rating too quickly this may anger politicians and commentators causing them to be blamed for the worsening crisis. A CRA taking prompt action in downgrading sovereign ratings may be viewed as a leader in ratings assignments.

[7] Alsakka *et al* (2014) find that although CRAs' *bank* rating assignments are independent during the pre-crisis period they become dependent during the GFC period with S&P's being the leader in terms of European bank rating downgrades.

[8] Applying ordered choice estimation methods to time-series data on the change in ratings that changes relatively infrequently means that securing converged estimates becomes increasingly difficult as more covariates are added to a model. Hence, we consider the CRAs in pairs with 2 variables in each equation rather than all 3 CRAs together with 3 regressors in each equation to ensure that valid estimation results can be obtained for as many countries as possible.

[9] https://www.**fitchratings**.com/web.../**ratings/sovereign_ratings_history**.xls *[Accessed 23 May, 2013]*
https://uvalibraryfeb.files.wordpress.com/2012/02/sovereignspratings2011dec.pdf [Accessed 23 May, 2013]
https://uvalibraryfeb.wordpress.com/2012/02/03/country-sovereign-ratings-moodys-fitch-sp/

data sample for Moody's sovereign ratings directly from the Agency. In Appendix 1, we provide the list of all countries in our sample with the corresponding 3 letter identifier. We select the countries to include in our analysis according to the following criteria. First, data is available for at least 2 CRAs for that country and second, the rating changes at least once for at least 2 CRAs for that country. Third, there are at least 60 overlapping observations for at least 1 *pair* of CRAs (this is because we use ordinal choice models that require large samples due to the nonlinear estimation method). Fourth, estimation converges and estimates are obtained for all coefficients in the test equations for a particular country. We denote the ratings assigned by Fitch, Moody's and S&P's with RF, RM and RS, respectively

4. Methodology

A Granger non-causality (GNC) style test is proposed for investigating the above hypotheses applied to the three pairs of CRAs' ratings. This method is particularly appropriate for examining herding because it tests for precedence and so allows one CRA to observe another CRA's assignment before making their assignment. A GNC-style method has been employed to analyse the lead-lag relationship between different CRAs' *bank* rating assignments by, for example, Alsakka *et al*'s (2014). The only previous application of a similar method to sovereign ratings is by Alsakka and ap Gwilym (2010), however, our work extends theirs, first, by allowing heterogeneity across countries (as well as through time) and, second, by controlling for habit behaviour when testing for herding.[10] Our results include tests applied to the 3 CRA pairings for each country – we are not aware of any previous analysis of credit rating herding that applies GNC-style tests for *individual* countries.

To illustrate the basic GNC-style test consider the following one lag bivariate autoregressive specification where ΔRX_{it} denotes the change in rating assignment made by CRA X for country i in time period t and ΔRY_{it} represents the change rating assignment made by CRA Y for the same country and time period. We use the change in rating assignment because it

[10] Alsakka and ap Gwilym (2010) apply ordered probit methods in their empirical investigation of the lead-lag linkage between different CRAs' *bank* rating assignments to data pooled across countries for CRA pairings in GNC-style regressions that exclude own lagged ratings (only the other CRA's past ratings appear as regressors). Hence, the exclusion of own lagged ratings may cause omitted variable bias. Our method ameliorates this possibility by including own lagged ratings.

reduces both the number of categories in the variables and the number of lags required in the model which reduces any problems in obtaining convergence in estimation.[11]

$$\Delta RX_{it}^{*} = \alpha_{1i}\Delta RX_{it-1} + \alpha_{2i}\Delta RY_{it-1} + u_{1it} \quad (1)$$

$$\Delta RY_{it}^{*} = \beta_{1i}\Delta RX_{it-1} + \beta_{2i}\Delta RY_{it-1} + u_{2it} \quad (2)$$

These equations are estimated individually by ordered probit methods using time-series regressions for each country.[12] Note that $Z_{it}^{*} = \Delta RX_{it}^{*}, \Delta RY_{it}^{*}$ denotes the unobserved dependent variable that is related to the observed dependent variable, $Z_{it} = \Delta RX_{it}, \Delta RY_{it}$, (assuming J categories) as follows:

$$\begin{aligned} Z_{it} &= 1 \quad if \quad Z_{it}^{*} \leq \Lambda_{1,\mathrm{i}} \\ Z_{it} &= j \quad if \quad \Lambda_{\mathrm{j}-1,\mathrm{i}} < Z_{it}^{*} \leq \Lambda_{\mathrm{j,i}} \\ Z_{it} &= J \quad if \quad \Lambda_{\mathrm{J}-1,\mathrm{i}} < Z_{it}^{*} \end{aligned}$$

where, $\mathrm{j} = 2, 3, \dots, \mathrm{J}$; $\Lambda_{\mathrm{j}-1,\mathrm{i}} = \lambda_{X,j-1,i}, \lambda_{Y,j-1,i}$ and $\lambda_{X,j-1,i}$ and $\lambda_{Y,j-1,i}$ are unknown limit points to be estimated with the coefficients in equation (1) and (2), respectively.

The basic interpretation of the GNC-style (and other exclusion tests) is:

(A) GNC-style tests:

[11] Given that ordinal data is bounded it is unlikely to exhibit significant nonstationarity. In particular, because ratings take on values between 1 and 20 the mean, if not constant, will be *converging* towards a constant and will certainly be finite. Further, the variance cannot be infinite given the boundaries on the values that a rating can take on and since the autoregressive covariances will not exceed the variance they will also be finite. Hence, we may regard ratings data as intrinsically covariance stationary and any high autoregressive (habit) coefficients found in the model will likely reflect that ratings change infrequently such that this period's rating often equals last period's value rather than nonstationarity. Nevertheless, to address the high persistence on the own lag variables (found in initial experiments based on OLS regressions) we use differenced data. This also helps overcome any residual autocorrelation evident in undifferenced data and reduces the number of categories that should help ensure convergence in estimation. Further, we note that for only 2 out of the 35 countries or 8 out of 150 equations for which (1) and (2) are estimated is the sample size below 100 observations which should also enhance our ability to obtain convergence in estimation.

[12] The use of ordered choice models recognises the ordinal nature of the dependent variables. We also consider pooled estimation of (1) and (2) to assess the heterogeneity of herding across countries with poolability tests.

(a) *Herding* occurs if CRA X (Y) *follows* Y's $(X's)$ previous assignment when making its current assignment, which is indicated by $\alpha_{2i} > 0$ $(\beta_{1i} > 0)$.[13]

(b) *Adverse herding* occurs if $\alpha_{2i} < 0$ $(\beta_{1i} < 0)$ because CRA X (Y) *reverses* Y's $(X's)$ previous assignment when making its current assignment.[14]

(c) There is *no significant herding* if CRA Y (X) does not temporally follow X's $(Y's)$ rating assignments, which is indicated by $\alpha_{2i} = 0$ $(\beta_{1i} = 0)$.

(B) Habit behaviour tests:

(a) *Habit rating assignment* (or *trend following*) occurs if $\alpha_{1i} > 0$ $(\beta_{2i} > 0)$ because CRA X (Y) *follows* its own previous assignment when making its current assignment.

(b) *Contrarian rating assignment* occurs if $\alpha_{1i} < 0$ $(\beta_{2i} < 0)$ because CRA X (Y) *reverses* its own previous assignment when making its current assignment.

(c) There is *no significant autocorrelation in a CRA's own rating assignment* if $\alpha_{1i} = 0$ $(\beta_{2i} = 0)$, that is, CRA X (Y) does not temporally follow its own rating assignments.

We use a model with only one lag because it gives an unambiguous interpretation in terms of the signs of coefficients of interest and thereby facilitates their interpretation within the above hypotheses. This lag length is also indicated by the Schwartz Information Criterion (SC) for the time-series regressions (see discussion below).

We use time-series regressions to examine the lead-lag relationship between ratings rather than pooling the countries together (as is done in, for examples, Guttler and Wahrenburg (2007) and Alsakka and ap Gwilym (2010)) because pooling assumes the homogeneity of (slope)

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[13] Within the context of security analysts recommending whether to buy, hold or sell a security with 5 possible recommendations (strong buy, buy, hold, sell, strong sell) Welch (2000) argues that it would not be surprising that many analysts' current extreme recommendations of strong sell or strong buy will subsequently move towards the consensus. It is suggested that there is a strong state dependence in the analysts' revision process such that the 5 (in this instance) probability vectors (for each recommendation) are not identical (except with different means). Hence, a positive correlation among analysts' recommendations may be expected without necessarily reflecting herding. However, such a criticism does not obviously apply to CRAs' assignments of sovereign ratings – for example, why should a highly (lowly) rated nation have some natural tendency away from that rating?

[14] The notion of adverse herding within the context of fund managers occurs when investors mistrust the market consensus of trades and so increase their reliance on their own judgment of asset prices – see, for example, Klein (2013, p. 295). Analogously, a CRA that assigns ratings in the opposite direction to another CRA is strongly disagreeing with that agency's evaluation of a rating assignment and is demonstrating increased confidence in their own judgment, which may be referred to as adverse herding.

coefficients across countries. If there are significant differences in slope coefficients across countries drawing inferences based upon pooled results can be misleading. To determine whether the use of a pooled estimator would be appropriate for our data and countries we apply the poolability test discussed in Kapetanious (2003) and Chortareas and Kaptenious (2009). To illustrate the method of this Hausman-style test we define the matrix of slope coefficients for country i in (1) as $\boldsymbol{\alpha}_i' = (\alpha_{1i}, \alpha_{2i})$. The hypotheses are:

$$H_0: \boldsymbol{\alpha}_i = \boldsymbol{\alpha} \qquad \forall\, i \tag{3}$$

$$H_1: \boldsymbol{\alpha}_i \neq \boldsymbol{\alpha} \qquad \text{for any } i \tag{4}$$

The test statistic for a given i is:

$$S_{Ti} = (\widehat{\boldsymbol{\alpha}}_i - \widetilde{\boldsymbol{\alpha}})' Var(\widehat{\boldsymbol{\alpha}}_i - \widetilde{\boldsymbol{\alpha}})^{-1} (\widehat{\boldsymbol{\alpha}}_i - \widetilde{\boldsymbol{\alpha}}) \tag{5}$$

where $\widehat{\boldsymbol{\alpha}}_i$ is the time-series estimated slope coefficient estimator for the given individual i and $\widetilde{\boldsymbol{\alpha}}$ is a consistent pooled data estimator that assumes homogeneity of slope coefficients (we will use the standard pooled ordered choice estimator given the generally large time-series dimension for each country). It is assumed that the estimators for both $\widehat{\boldsymbol{\alpha}}_i$ and $\widetilde{\boldsymbol{\alpha}}$ are consistent and asymptotically normal and that the estimator for $\widetilde{\boldsymbol{\alpha}}$ is also efficient under the poolability null hypothesis.

Even though the variance is not assumed to be efficient Chortareas and Kaptenious (2009) argue that as $N \to \infty$ $Cov(\widehat{\boldsymbol{\alpha}}_i, \widetilde{\boldsymbol{\alpha}})$ will become negligible such that (6) may be used to estimate $Var(\widehat{\boldsymbol{\alpha}}_i - \widetilde{\boldsymbol{\alpha}})$ based upon a consistent estimator of $Var(\widehat{\boldsymbol{\alpha}}_i)$. We use the Huber White (QML) robust coefficient variances and covariance estimators in both pooled and time-series regressions.[15]

$$Var(\widehat{\boldsymbol{\alpha}}_i - \widetilde{\boldsymbol{\alpha}}) = Var(\widehat{\boldsymbol{\alpha}}_i) + Var(\widetilde{\boldsymbol{\alpha}}) \tag{6}$$

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[15] Hence, for our application the test statistic is: $S_{Ti} = \left(\begin{bmatrix}\hat{\alpha}_{1i}\\ \hat{\alpha}_{2i}\end{bmatrix} - \begin{bmatrix}\tilde{\alpha}_1\\ \tilde{\alpha}_2\end{bmatrix}\right)' \left\{Var\begin{bmatrix}\hat{\alpha}_{1i}\\ \hat{\alpha}_{2i}\end{bmatrix} + Var\begin{bmatrix}\tilde{\alpha}_1\\ \tilde{\alpha}_2\end{bmatrix}\right\}^{-1} \left(\begin{bmatrix}\hat{\alpha}_{1i}\\ \hat{\alpha}_{2i}\end{bmatrix} - \begin{bmatrix}\tilde{\alpha}_1\\ \tilde{\alpha}_2\end{bmatrix}\right)$,
$\Rightarrow S_{Ti} = Det \times [(\hat{\alpha}_{1i} - \tilde{\alpha}_1)^2\{Var(\hat{\alpha}_{2i}) + Var(\tilde{\alpha}_2)\} - 2(\hat{\alpha}_{1i} - \tilde{\alpha}_1)(\hat{\alpha}_{2i} - \tilde{\alpha}_2)\{Cov(\hat{\alpha}_{1i}, \hat{\alpha}_{2i}) + Cov(\tilde{\alpha}_1, \tilde{\alpha}_2)\} + (\hat{\alpha}_{2i} - \tilde{\alpha}_2)^2\{Var(\hat{\alpha}_{1i}) + Var(\tilde{\alpha}_1)\}]$, where $Det = \left[\frac{1}{\{Var(\hat{\alpha}_{1i}) + Var(\tilde{\alpha}_1)\}\{Var(\hat{\alpha}_{2i}) + Var(\tilde{\alpha}_2)\} - \{Cov(\hat{\alpha}_{1i}, \hat{\alpha}_{2i}) + Cov(\tilde{\alpha}_1, \tilde{\alpha}_2)\}^2}\right]$.

Chortareas and Kaptenious (2009) suggest that the asymptotic distribution of S_{Ti} for a given i is (where k denotes the number of slope coefficients):

$$S_{Ti} \xrightarrow{d} \chi_k^2 , \qquad T \to \infty \tag{7}$$

Although a statistic $S_T^S = sup_i S_{Ti}$ is developed to test the poolability null, equation (3), it is noted that using S_T^S is not necessary to conduct the test. A large individual S_{Ti} is sufficient to reject the null. We therefore calculate S_{Ti} for each country and find evidence against poolability if the null is rejected for any i. If poolability is rejected this implies that time-series regressions should be used for each country to allow heterogeneity of parameters and thereby produce reliable results.

The above GNC-style tests provide answers to Hypothesis 1 and Hypothesis 2. To assess Hypothesis 3 we use shift dummy variables to allow coefficients to change at the pre-identified break point and conduct the GNC-style tests for both pre- and post-break periods without losing as many degrees of freedom as would be the case with sample splitting.[16] To enable the application of the test we only consider splitting the sample into two sub-periods. A predetermined period is appropriate for assessing any changes in the degree of herding in different environmental states (such as before and after the GFC). To test whether the herding coefficients change after the GFC (we approximate this with the break point being between May 2007 and June 2007 following Lugo et al 2014) based upon time-series regressions we define the following dummy variable as:[17]

$$D_{it} = \begin{cases} 0 & t \leq May\ 2007 \\ 1 & t \geq June\ 2007 \end{cases} \tag{8}$$

The modified specification used to test for parameter non-constancy is based upon:

[16] This test would not be able to identify a situation where the leading rating agency is frequently changing through time. However, a frequently changing leader agency would be very difficult to observationally distinguish from no rating assignment leadership behaviour. Further, it is likely that for many countries there is some degree of rating inertia such that rating changes are relatively infrequent. Hence, it is unlikely that there would be a large number of changes in leadership through time simply because there are comparatively few rating changes.
[17] We use this sample break point to ensure that the first crisis based downgrades in sovereign ratings that occurred late in 2007 are in our definition of the crisis period.

$$\Delta RX_{it}^{*} = \alpha_{1i}\Delta RX_{it-1} + \delta_{1i}(D_{it} \times \Delta RX_{it-1}) + \alpha_{2i}\Delta RY_{it-1} + \delta_{2i}(D_{it} \times \Delta RY_{it-1}) + u_{1it} \quad (9)$$

$$\Delta RY_{it}^{*} = \beta_{1i}\Delta RX_{it-1} + \gamma_{1i}(D_{it} \times \Delta RX_{it-1}) + \beta_{2i}\Delta RY_{it-1} + \gamma_{2i}(D_{it} \times \Delta RY_{it-1}) + u_{2it} \quad (10)$$

The hypothesis tests that we consider are:[18]

(C) GNC-style tests:

(a) *Herding* behaviour of CRA X (Y) *exhibits a significant change* during the GFC if $\delta_{2i} \neq 0$ $(\gamma_{1i} \neq 0)$.

(i) When $\delta_{2i} > 0$ $(\gamma_{1i} > 0)$ *the degree of herding* of CRA X (Y) *has increased*.

(ii) When $\delta_{2i} < 0$ $(\gamma_{1i} < 0)$ *the degree of herding* of CRA X (Y) *has decreased*.

(b) *Herding* behaviour of CRA X (Y) *exhibits no significant change* during the GFC if $\delta_{2i} = 0$ $(\gamma_{1i} = 0)$.

The herding coefficients up to and including May 2007 are α_{2i} and β_{1i} and (strictly) after May 2007 are $\alpha_{2i} + \delta_{2i}$ and $\beta_{1i} + \gamma_{1i}$.[19]

5. Results

This section discusses the following results in order: pooled regressions and poolability tests, full period individual country regressions, split sample individual country regressions.

5.1 Pooled regressions and poolability tests

[18] The focus of our attention will be on changes in herding behaviour and we do not present an investigation of changes in the habit coefficients.

[19] Because the coefficients after the change are a sum of two values, t-tests for whether a coefficient is statistically significant after the change require the variance of that sum to be calculated. This test can be implemented as follows. For generality denote the sum of coefficients as $\theta_{ki} + \varphi_{ki}$, where $\theta_{ki} = \alpha_{ki}, \delta_{ki}$ and $\varphi_{ki} = \beta_{ki}, \gamma_{ki}$ with $k = 1, 2$. The hypotheses to be tested are, $H_0\colon \theta_{ki} + \varphi_{ki} = 0$; $H_1\colon \theta_{ki} + \varphi_{ki} \neq 0$. The t-statistic is: $t = \frac{\hat{\theta}_{ki} + \hat{\varphi}_{ki}}{\sqrt{Var(\hat{\theta}_{ki} + \hat{\varphi}_{ki})}}$, where, $Var(\hat{\theta}_{ki} + \hat{\varphi}_{ki}) = Var(\hat{\theta}_{ki}) + Var(\hat{\varphi}_{ki}) + 2Cov(\hat{\theta}_{ki}\hat{\varphi}_{ki})$.

Previous analyses of the lead-lag relationship between CRAs pool all countries together in one regression – see Alsakka and ap Gwilym (2010). We therefore start by estimating (1) and (2) for all 3 pairs of CRAs using pooled ordered probit regressions and the results are reported in Table 1. The probability value of the likelihood ratio statistic, p[LR], is less than 0.050 in all cases suggesting that the hypothesis that all regression coefficients are zero is rejected for all 6 equations. Further, the GNC (herding) coefficient is significant and positive at the 5% level in all 6 equations. This suggests bi-directional Granger-causality for all three rating agency pairings. That is, Fitch follows Moody's ratings and Moody's follows Fitch's ratings while Fitch follows S&P's ratings and S&P's follows Fitch's ratings. Similarly, Moody's follows S&P's ratings and S&P's follows Moody's ratings. These results suggest that all of the CRAs herd towards each others' ratings with no clear leader or follower. The habit coefficient is positive and significant for only 2 of the 6 equations: on Fitch's autoregressive coefficient when Moody's is the other CRA and on S&P's autoregressive coefficient when Moody's is the other CRA. This suggests that these CRAs are influenced by their own previous rating assignments.

However, because the models are estimated using data pooled across all countries it is possible that there is heterogeneity of the lead/lag relationships across countries that is not apparent in the pooled regressions. This is confirmed by the poolability test statistic, S_T^S, that rejects the poolability of the data across countries for all 6 equations and suggests that the models estimated for the individual countries will typically yield different coefficients from those obtained from pooled estimation.

Further, poolability is rejected if any one of the individual country's poolability test statistics, S_{Ti}, exceeds the 5% critical value. The individual country poolability tests are reported in Table 2. They reject the poolability null for 19 out of 24 (79%) countries when ΔRF_{it}, denoting the change in Fitch's rating, is the dependent variable and in 15 out of 24 (63%) countries when ΔRM_{it}, the change in Moody's assignment, is the dependent variable for the CRA pairing of Fitch and Moody's. The poolability null is rejected for 8 out of 28 (29%) countries when ΔRF_{it} is the dependent variable and in 11 out of 28 (39%) countries when ΔRS_{it}, the change in S&P's rating, is the dependent variable for the CRA pairing of Fitch and S&P's. The poolability null is rejected for 8 out of 23 (35%) countries when ΔRM_{it} is the dependent variable and in 14 out of 23 (61%) countries when ΔRS_{it} is the dependent variable for the CRA pairing of Moody's and S&P's. Overall, 75 out of 150 (49%) individual poolability tests are rejected and poolability is rejected in each equation for each country pairing suggesting clear rejection of the poolability null and the need to estimate models country by country to reveal the heterogeneity across countries.

5.2 Full period individual country regressions

We therefore proceed to consider the time-series estimation of (1) and (2) for each CRA pairing for each individual country. To determine whether one lag of each variable in each equation is sufficient we estimate versions of (1) and (2) with 1, 2, 3 and 4 lags on each variable using the same sample period (to ensure comparability) for each CRA pairing and country and select the lag length based on the equation that has the minimum SC. Table 3 reports the SC for Fitch and Moody's and both equations for all 24 countries indicate 1 lag except for Greece with ΔRM_{it} as the dependent variable that indicates 2 lags. Table 4 reports the SC for Fitch and S&P's and both equations for all 28 countries indicate 1 lag except for Romania with ΔRF_{it} as the dependent variable that indicates 2 lags. Table 5 reports the SC for Moody's and S&P's and both equations for all 23 countries indicate 1 lag according except for Latvia with ΔRM_{it} as the dependent variable that indicates 3 lags. Thus, 147 out of the 150 (98%) estimated equations indicate 1 lag. This suggests strong support for estimating all models with a lag length of 1. We therefore estimate equations (1) and (2) using the full available time-series sample to test our hypotheses.

Table 6 reports results for the Fitch and Moody's CRA pairing. For 4 countries (ARG, CYP, ITA and LIT) there is a positive and significant (at the 5% level) coefficient on ΔRM_{it-1} in the equation where ΔRF_{it} is the dependent variable indicating that Fitch's current rating follows (herds towards) last period's rating assigned by Moody's. For no countries is this coefficient negative and significant indicating that Fitch's current rating does not move away from (adverse herd against) Moody's rating assigned last period for any country. Indeed, there are no instances of any CRA engaging in significant adverse herding against any other CRA for any pairing in any country. For 4 countries (ICE, LAT, RUS and TUR) there is evidence that Moody's current rating follows (herds towards) Fitch's rating assigned last period. These results suggest the unambiguous inference that Moody's is the leader and Fitch is the follower for 4 countries

(ARG, CYP, ITA and LIT) and that Fitch is the leader and Moody's is the follower for 4 countries (ICE, LAT, RUS and TUR).

For 3 countries (ARG, ICE and RUS) there is a positive and significant coefficient on ΔRF_{it-1} in the equation where ΔRF_{it} is the dependent variable suggesting that Fitch tends to follow its own past rating in making its current assignment (habit behaviour) for these countries. It is notable that in 2 of these countries (ICE and RUS) there is evidence that Moody's follows Fitch's rating confirming the independence of Fitch in making assignments for these countries. In 1 country (ITA) there is a negative and significant coefficient on ΔRF_{it-1} in the equation where ΔRF_{it} is the dependent variable suggesting that Fitch tends to reverse its own past rating in making its current assignment (contrarian habit behaviour) for this country. In this country there is evidence that Fitch follows Moody's rating confirming Fitch's tendency to herd towards Moody's (rather than their own) rating in making their assignment for this country. For 1 country (URU) there is evidence of habit behaviour in Moody's assignment and for 1 country (ROM) there is evidence of significant contrarian habit behaviour by Moody's.

Table 7 reports results for the Fitch and S&P's CRA pairing. For 10 countries (CYP, DOM, ECU, GRE, INO, IRE, JAM, POR, SPA and TUR) there is a positive and significant coefficient on ΔRS_{it-1} in the equation where ΔRF_{it} is the dependent variable indicating that Fitch's current rating follows (herds towards) last period's rating assigned by S&P's. For 6 countries (GRE, HOG, ICE, INO, RUS and URU) there is evidence that S&P's current rating follows (herds towards) Fitch's rating assigned last period. These results suggest the unambiguous inference that S&P's is the leader and Fitch is the follower for 8 countries (CYP, DOM, ECU, IRE, JAM, POR, SPA and TUR) and that Fitch is the leader and S&P's is the follower for 4 countries (HOG, ICE, RUS and URU). For GRE and INO the evidence suggest bi-directional Granger-causality where S&P's appears to follow Fitch's past ratings while Fitch simultaneously follows S&P's past rating assignment. Two points about these inferences are worth noting. First, the coefficient on ΔRS_{it-1} in the equation where ΔRF_{it} is the dependent variable is more than (less than) that of the coefficient on ΔRF_{it-1} in the equation where ΔRS_{it} is the dependent variable suggesting that Fitch's (S&P's) tendency to follow S&P's (Fitch's) past rating assignment is greater than the other way around for GRE (INO). Second, these results might indicate a change in rating leadership through time for these countries. This issue may be assessed by consideration of whether the models' coefficients change through time.

For 4 countries (ARG, ICE, INO and RUS) there is a positive and significant coefficient on ΔRF_{it-1} in the equation where ΔRF_{it} is the dependent variable suggesting that Fitch tends to follow its own past rating in making its current assignment (habit behaviour) for these countries. It is notable that in 2 of these countries (ICE and RUS) there is unambiguous evidence that S&P's follows Fitch's rating confirming the independence of Fitch in making assignments for these countries. In no countries is there a negative and significant coefficient on ΔRF_{it-1} in the equation where ΔRF_{it} is the dependent variable suggesting that Fitch does not tend to reverse its own past rating in making its current assignment (contrarian habit behaviour) for any country. For 2 countries (ECU and POR) there is evidence of habit behaviour in S&P's assignment while for 2 countries (BRA and URU) there is evidence of significant contrarian habit behaviour by S&P's. In both ECU and POR there is evidence that Fitch follows S&P's rating confirming the independence of S&P's in making assignments for these countries. For URU the contrarian habit behaviour by S&P's coincides with, and is confirming of, the evidence that S&P's tends to herd towards Fitch's assignments for this country.

Table 8 reports results for the Moody's and S&P's CRA pairing. For 14 countries (ARG, ECU, GRE, ICE, INO, IRE, JAM, NEW, PHI, POR, ROM, SLO, THA and VEN) there is a positive and significant coefficient on ΔRS_{it-1} in the equation where ΔRM_{it} is the dependent variable indicating that Moody's current rating follows (herds towards) last period's rating assigned by S&P's. For 5 countries (ARG, CYP, INO, RUS and SLO) there is evidence that S&P's current rating follows (herds towards) Moody's rating assigned last period. These results suggest the unambiguous inference that S&P's is the leader and Moody's is the follower for 11 countries (ECU, GRE, ICE, IRE, JAM, NEW, PHI, POR, ROM, THA and VEN) and that Moody's is the leader and S&P's is the follower for 2 countries (CYP and RUS). For 3 countries (ARG, INO and SLO) the evidence suggest bi-directional Granger-causality where S&P's appears to follow Moody's past ratings while Moody's simultaneously follows S&P's past rating assignment. We note that the coefficients on ΔRM_{it-1} in the equations where ΔRS_{it} is the dependent variable are more than (less than) the coefficients on ΔRS_{it-1} in the equations where ΔRM_{it} is the dependent variable for ARG and INO (SLO) suggesting that S&P's (Moody's) tendency to follow Moody's (S&P's) past rating assignment is greater than the other way around for these countries. This bi-directional causality might indicate a change in rating assignment leadership through time for these countries.

For 2 countries (THA and URU) there is a positive and significant coefficient on ΔRM_{it-1} in the equation where ΔRM_{it} is the dependent variable suggesting that Moody's tends to follow its own past rating in making its current assignment (habit behaviour) for this country. In 1 of these countries (THA) there is unambiguous evidence that S&P's follows Moody's rating perhaps confirming the independence of Moody's in making assignments for this country. In 3 countries (ICE, JAM and ROM) there is a negative and significant coefficient on ΔRM_{it-1} in the equation where ΔRM_{it} is the dependent variable suggesting that Moody's tends to reverse its own past rating in making its current assignment (contrarian habit behaviour) for these countries. In all 3 of these countries there is unambiguous evidence that Moody's follows S&P's rating confirming Moody's tendency to herd towards S&P's (rather than its own) rating in making its assignment for these countries. For 4 countries (ECU, ICE, POR and SLO) there is evidence of habit behaviour in S&P's assignment however there is no evidence of significant contrarian habit behaviour by S&P's for any country. In ECU, ICE, POR and SLO there is evidence that Moody's follows S&P's rating confirming the independence of S&P's in making assignments for these countries. This conclusion is reinforced for ICE because there is evidence that Moody's engages in contrarian habit behaviour for this country.

Overall there is evidence of leadership/follower behaviour between Fitch and Moody's for 8 out of 24 (33%) countries, between Fitch and S&P's in 14 out of 28 (50%) countries and between Moody's and S&P's for 16 out of 23 (70%) countries.[20] As might be expected S&P's is the leader for more countries than the other CRAs although it is not the leader for all countries. Perhaps unexpectedly Fitch is not less of a leader or more of a follower than Moody's.

Table 9 summarises the full-sample individual GNC results by country for all 3 CRAs to provide insights into the distribution of leadership across the 3 CRAs for each country. The notation used in the table is as follows. If a CRA unambiguously leads the other for any pairing for a particular country this is indicated with the letter "L" in that CRA's column. If there is bi-directional Granger-causality (dual leadership) this is indicated with an "L" in the column headed "Dual". The CRA with the largest GNC coefficient when there is bi-directional Granger-causality is indicated with the symbol "F" (Fitch), "M" (Moody's) or "S" S&P's in the "Dual" column. The absence of leadership is indicated by a blank entry while "-" indicates that

[20] There is evidence of habit behaviour or contrarian habit behaviour between Fitch and Moody's in 6 out of 24 (25%) countries, between Fitch and S&P's for 8 out of 28 (29%) countries and between Moody's and S&P's in 8 out of 23 (35%) countries.

estimation results are unavailable for a particular CRA pairing in a specific country. When a CRA's leadership is confirmed by it exhibiting positive habit behaviour this is indicated by "H*", where * denotes F for Fitch, M for Moody's and S for S&P's. Leadership that is reinforced by contrarian habit behaviour is denoted with "C*".

From Table 9 there is no evidence of any CRA leading or following another CRA for 11 of the 35 countries which at first sight appears to suggest an absence of herding for many (almost one third) of the nations considered. However, for only one of these countries (BRA) are results on leadership available for all 3 CRAs which means that such a conclusion could be partly due to missing information rather than a complete lack of herding. For 4 countries (ECU, IRE, JAM and POR) there is evidence that S&P's leads both Fitch and Moody's without any evidence that S&P's follows either of these CRAs indicating that S&P's is the clear leader for these countries. In none of these countries is this conclusion due to missing information because results are available for all 3 CRAs in each case.[21] For 3 countries (ICE, RUS, and TUR) there is evidence that Fitch leads both Moody's and S&P's without any evidence that Fitch follows either of these CRAs. However, in one of these countries (TUR), this conclusion involves missing information because the results are not available for Moody's and S&P's. Neverthelss, in this case, our results still provide strong evidence that Fitch is the clear leader for these 3 countries.[22] For 1 country (CYP) there is evidence that Moody's leads Fitch and S&P's without any evidence that Moody's follows either of these CRAs suggesting that Moody's is the clear leader for this country.[23] This way of presenting the evidence confirms the conclusions drawn above that S&P's is the unambiguous leader for more countries than the other CRAs which is consistent with the prior belief that this is because this is most established CRA with greatest reputational capital. The inference that Fitch exhibits unambiguous more leadership than Moody's also confirms the conclusions from the discussion above however it is not consistent with our prior belief that Fitch is likely to have the least reputational capital. This latter conclusion may be due to our consideration of only a subset of countries that are rated and that it is not representative of the

[21] In 1 of these countries (POR) there is evidence that Fitch also leads Moody's suggesting that there is a clear order of leadership for Portugal: S&P's, Fitch, Moody's.

[22] For ICE there is also evidence that S&P's leads Moody's suggesting the order of leadership for Iceland is Fitch, S&P's and Moody's; while for RUS the evident order of leadership is Fitch, Moody's and S&P's.

[23] For CYP there is also evidence that S&P's leads Fitch suggesting the order of leadership for Iceland is Moody's, S&P's and Fitch.

population or it may be that for sovereign ratings over the period considered that Moody's is the primary follower in ratings assignments.[24]

5.3 Split sample individual country regressions

Table 10 reports the results of individual country regressions that allow both slope coefficients to change between 2007M05 and 2007M06 – equations (9) and (10). For some countries ordered probit models could not be estimated, therefore, results are only reported for 8 countries for the Fitch and Moody's CRA pairing, for 12 countries for the Fitch and S&P's CRA pairing and for 9 countries for the Moody's and S&P's CRA pairing. Whilst only providing a partial picture of any changes in herding behaviour, (we only report results on the herding coefficients because this is the focus of our interest), the results provide interesting indicative insights into the issues that we wish to consider. The columns headed GNC-pre and GNC-post denote the Granger causality (herding) coefficient before and after the break point, respectively, with the adjacent columns, denoted P[t(h)], giving the probability value of a t-test for the significance of the associated coefficient and P(break) is the probability value of a t-test for the significance of the break.[25]

For 3 countries (LAT, LIT and POR) there is evidence of a significant change in the coefficient on ΔRM_{it-1} in the equation where ΔRF_{it} is the dependent variable – see P(break). In all 3 cases the coefficient declines indicating that Fitch's tendency to follow (herd towards) Moody's rating last period falls after the break for these 3 countries. Nevertheless, Fitch still exhibits significant herding after the break for 1 country (LIT). For 1 country (LAT) the coefficient on ΔRF_{it-1} changes significantly in the equation where ΔRM_{it} is the dependent variable such that the coefficient that is insignificant before the break becomes significant after

[24] For the remaining countries unidirectional leadership is indicated as follows (we do not highlight any dual leadership). For GRE, NEW, PHI, ROM, THA and VEN S&P's leads Moody's while for DOM and SPA S&P's leads Fitch with no other unidirectional leadership indicated. For HOG and URU Fitch leads S&P's with no other unidirectional leadership indicated. For ARG, ITA and LIT Moody's leads Fitch with no other unidirectional leadership indicated. For LAT Fitch leads Moody's with no other unidirectional leadership indicated. When considering these conclusions it should be borne in mind that results were not available for all 3 CRA pairings for HOG, ITA, NEW, PHI, SPA and THA.

[25] The post-break coefficient is calculated as the sum of the pre-break coefficient and the change in the coefficient between the two periods while the t-test for the significance of the post-break coefficient is for the null hypothesis that the sum of the pre-break coefficient and change coefficient is zero. P(break) is the probability value for the null hypothesis that the change coefficient is zero.

the break. This increase implies that Moody's tendency to follow Fitch's rating last period rises after the break indicating evident intentional herding in this country. These results suggest that while there is only a significant change in 4 out of 16 instances they all indicate an increase in Moody's tendency to follow Fitch and a decrease in Fitch's inclination to herd towards Moody's ratings after the break.

For 3 countries (IRE, LIT and POR) there is evidence of a significant change in the coefficient on ΔRS_{it-1} in the equation where ΔRF_{it} is the dependent variable. In all 3 cases the coefficient rises indicating that Fitch's tendency to follow S&P's rating last period increases after the break for these 3 countries and in 2 cases (LIT and SPA) the coefficient changes from insignificant before the break to significantly positive after the break, suggesting intentional herding. For a further 4 countries (ECU, GRE, POR and RUS) there is evidence that Fitch intentionally herds towards S&P's rating because the coefficient changes from insignificant before the break to significantly positive after the break, even though the change in the coefficient is not significant. For 1 country (KAZ) the coefficient on ΔRF_{it-1} changes significantly in the equation where ΔRS_{it} is the dependent variable such that the coefficient that is insignificant before the break becomes significant and positive after the break. This increase indicates that S&P's tendency to follow Fitch's rating last period rises after the break suggesting intentional herding in this country. Conversely, for 3 countries (GRE, POR and RUS) the coefficient that is positive and significant prior to the break becomes insignificant after the break which, even though the change in coefficient is not significant, is indicative of a reduction in any tendency by S&P to herd towards Fitch (any apparent herding is unintentional). It is interesting to be reminded that the results in Table 7 indicated dual leadership (Granger-causality) for Greece when the models were estimated over the full sample. By splitting the sample our results imply that leadership changed for this country from Fitch being the leader prior to the break to S&P becoming the leader after the break. This highlights the importance of considering heterogeneity of leadership through time as well as across countries.[26] These results generally suggest an increase in Fitch's inclination to (intentionally) herd towards S&P's rating after the break rather than the other way around.

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[26] Our results in Table 10 do not include any other countries for which dual leadership (Granger-causality) is indicated in Table 6 – 8.

For 4 countries (CYP, IRE, LIT and POR) there is evidence of a significant change in the coefficient on ΔRS_{it-1} in the equation where ΔRM_{it} is the dependent variable. In all 4 cases the coefficient rises from insignificant before the break to significantly positive after the break suggesting Moody's tendency to intentional herd towards S&P's previous rating. For a further 2 countries (ECU and LAT) there is evidence that Moody's intentionally herds towards S&P's rating because the coefficient changes from insignificant before the break to significantly positive after the break, even though the change in the coefficient is not significant. [27] For 1 country (POR) the coefficient on ΔRM_{it-1} changes significantly in the equation where ΔRS_{it} is the dependent variable such that the coefficient that is positive and significant before the break becomes insignificant after the break. This reduction implies that S&P's tendency to follow Moody's previous rating falls after the break indicating that any apparent herding by S&P's is unintentional in this country. Nevertheless, there is 1 country (CYP) where the herding coefficient that is insignificant prior to the break becomes positive and significant after the break which, even though the change in coefficient is not significant, is indicative of an increase S&P's tendency to intentionally herd towards Moody's rating. However, in CYP there is bi-directional causality where the post break coefficient is greater on ΔRS_{it-1} than ΔRM_{it-1} which possibly suggests a greater tendency for Moody's to (intentionally) herd towards S&P's than the other way around. [28] These results generally indicate an increase in Moody's inclination to (intentionally) herd towards S&P's rating after the break rather than the other way around.

Overall, the CRA's appear to make independent rating assignments for the majority of countries as should be expected of autonomous agencies. However, there is evidence of intentional herding for some countries and in the vast majority of cases it is Fitch and Moody's that intentionally herd towards S&P's. This would be consistent with our prior expectation that, to the extent that there is intentional herding, it is towards the main agency with the most reputational capital (S&P's). However, we do not find any evidence of Fitch (that might be expected to have the least reputational capital) being engaged in notably greater intentional herding than Moody's.

6. Conclusion

[27] Whilst there is no significant change for GRE the herding coefficient increases after the break (it is significant in both periods) further confirming Moody's increasing inclination to follow S&P's assignments after the break.

[28] This result may indicate that there is a change leadership in the post-break period.

We assess herding by considering the lead-lag relationship of sovereign ratings assigned by the 3 main CRAs. The only previous study of the lead-lag relationship for sovereign ratings (Alsakka and ap Gwilym, 2010) used pooled data methods that assume this lead-lag relationship is homogeneous across countries. Our pooled estimation results suggest bi-directional Granger-causality for all three CRA pairings implying that all of the CRAs herd towards each others' ratings with no clear leader or follower.

Given that different CRAs may have dissimilar levels of expertise and reputational capital for different countries it is not obvious that such homogeneity holds. We therefore are the first to conduct poolability tests within this context to assess this assumption and find evidence of heterogeneity (refuting Hypothesis 1) and thereby extend the literature on herding among CRAs' sovereign assignments. This leads us to conduct country-by-country time-series tests to assess the lead-lag relationship among agencies and, to our knowledge, we are the first to do this for sovereign ratings.

These results suggest an absence of herding across the CRAs for almost one third of the 35 countries that we consider. They also indicate that no one CRA is the leader for all countries where herding is apparent. Nevertheless, they do suggest that S&P's is the leader for more countries than the other CRAs which is consistent with the prior belief that S&P's is the most established CRA with greatest reputational capital. We also find that Fitch exhibits leadership for more countries than Moody's which is unexpected because Fitch may be regarded as the CRA possessing the least reputational capital.

To assess the extent to which any herding is intentional we also consider changes in the lead-lag relationship through time by splitting the sample into pre-crisis and crisis periods. Our results indicate that this relationship changes through time for some countries (refuting Hypothesis 2 and supporting Hypothesis 3) and when it does it typically changes such that S&P's ratings are followed in the crisis period. Hence, in the vast majority of countries where herding is found to be intentional it is Fitch and Moody's that intentionally herd towards S&P's. This further confirms our expectations given that S&P's is regarded as possessing the greatest reputational capital.

These findings contribute to an ongoing debate about the regulatory implications for CRAs and the openness of the market for new entrants. Although we cannot confirm the herding behaviour in all cases, it is evident that S&P's has a dominant position in the market. The remaining two agencies then often follow the leading agency. Thus CRAs do not collude perfectly. S&P's differentiates itself from the other two CRAs in terms of ratings quality. However, this differentiation in ratings quality is not observable by market participants since Moody's and Fitch Ratings identify themselves with S&P's. Such a finding raises doubts about the independent judgment of CRAs as pointed out by White (2010).

The presence of herding behaviour among CRAs undermines the exclusive position of CRAs as 'safety' judgments about credit risk which have the force of law. In addition, greater information disclosure about the rating assignments of CRAs would contribute to higher objectivity of the rating process. That would bring a certain degree of competition among CRAs and motivate them to design more reliable models. Cantor and Packer (1996) show that risks of sovereign credit ratings reflect macroeconomic fundamentals. In other words, CRAs could distinguish themselves by providing better and more reliable ratings as discussed by Opp, Opp and Harris (2013).

Extension of our research could be directed in several ways. One unanswered question is whether all three CRAs use the same quantitative determinants with the same weights for sovereign rating assignments. In other words, it would be desirable to assess and compare how reliable the models are for predicting sovereign ratings. This could also be done so as to distinguish between emerging markets and developed economies. This could help explain the reputational effects of CRAs and provide insights into why CRAs herd. A further research question closely related to our study is to investigate whether herding behaviour is evident in rating assignments of other instruments like Credit Default Swaps or Corporate Bonds. Finally, there is also scope for addressing methodological issues such as the consideration of all 3 CRAs simultaneously, rather than in pairs, to assess herding. This would require increased time-series sample sizes to feasibly implement country-by-country, which may become possible as time passes and more data becomes available.

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Appendix 1

The 35 countries (with their associated country identifier given in parentheses) are: Argentina (ARG), Bahrain (BAR), Brazil (BRA), Cyprus (CYP), Czech Republic (CZE), Dominican Republic (DOM), Ecuador (ECU), Estonia (EST), Greece (GRE), Hong Kong (HOG), Hungary (HUN), Iceland (ICE), Indonesia (INO), Ireland (IRE), Italy (ITA), Jamaica (JAM), Kazakhstan (KAZ), South Korea (KOR), Latvia (LAT), Lebanon (LEB), Lithuania (LIT), New Zealand

(NEW), Peru (PER), Philippines (PHI), Portugal (POR), Romania (ROM), Russia (RUS), Slovakia (SLO), Slovenia (SLV), Spain (SPA), Thailand (THA), Turkey (TUR), Ukraine (UKR), Uruguay (URU), Venezuela (VEN).

Table 1: Pooled GNC ordered probit regressions

Dependent variable	ΔRF_{it}	ΔRM_{it}	ΔRF_{it}	ΔRS_{it}	ΔRM_{it}	ΔRS_{it}
GNC	0.382	0.362	0.503	0.451	0.631	0.339
	(4.403)***	(4.243)***	(6.365)***	(3.856)***	(7.795)***	(3.739)***
Habit	0.217	0.052	0.059	0.034	0.044	0.235
	(2.544)**	-0.396	-0.349	-0.338	-0.377	(2.586)***
Pseudo-R^2	0.022	0.012	0.036	0.023	0.051	0.016
p[LR]	0	0	0	0	0	0
N	24	24	28	28	23	23
Observations	3911	3908	4715	4715	4638	4641
S_T^S	48.198**	28.797**	38.537**	17.505**	42.834**	27.330**

Table notes. Each equation (in each column) is estimated using ordered probit regression with all countries pooled together in each model. Dependent variable indicates the regressand in the relevant two variable system of equations to which the results refer. GNC denotes the Granger causality (herding) coefficient while Habit represents the autoregressive (habit) coefficient. Figures in brackets are t-ratios based on Huber-White robust standard errors. Significance at the 1% level is indicated with ***, at the 5% level with **, and at the 10% level with *. Pseudo-R^2 denotes the pseudo-R^2 statistic and p[LR] represents the probability value of the LR statstic for the null that all slope coefficients are zero. Observations give the total number of observations used in the estimation of the pooled models while N represents the number of countries included in each pooled regression. S_T^S denotes the maximum value of Chortareas and Kapetanios's (2009) poolability test statistic – it is the maximum value of the individual country statistics. The 5% critical values with (k =) 2 slope coefficients are 11.948 (N=20), 12.328 (N=25) and 12.785 (N=30) - see Table 1 in Kapetanios (2003, p. 14). In our applications with N = 24, N = 28 and N = 23 the approximate 5% critical values for S(sup) are: 12.252, 12.602 and 12.176, respectively. Rejection of poolability is indicated by **.

Table 2: Individual country poolability test statistics (ordered probit regressions)

	Dependent variable			Dependent variable			Dependent variable	
Country	ΔRF_{it}	ΔRM_{it}	Country	ΔRF_{it}	ΔRS_{it}	Country	ΔRM_{it}	ΔRS_{it}
ARG	1.182	0.046	ARG	9.441**	0.959	ARG	0.422	1.541
BAR	23.225**	15.881**	BRA	1.993	4.503	BAR	42.834**	21.270**
BRA	22.035**	16.104**	CYP	2.001	15.575**	BRA	2.319	16.851**
CYP	5.921	17.153**	CZE	26.474**	10.280**	CYP	1.447	4.79
DOM	6.117**	18.608**	DOM	5.499	0.132	DOM	3.265	8.970**
ECU	8.719**	8.475**	ECU	1.237	17.505**	ECU	0.263	3.085
GRE	12.830**	0.494	EST	0.95	1.669	GRE	0.077	3.276
HUN	48.198**	28.797**	GRE	2.118	0.488	ICE	10.035**	11.112**
ICE	7.921**	3.208	HOG	15.289**	3.819	INO	3.603	7.180**
INO	2.374	0.12	ICE	3.717	7.861**	IRE	6.963**	11.011**
IRE	36.233**	21.914**	INO	5.064	3.04	JAM	7.621**	21.218**
ITA	7.046**	5.326	IRE	9.504**	0.464	LAT	0.746	0.861
JAM	27.302**	22.832**	JAM	5.872	12.835**	LIT	1.247	21.081**
LAT	7.519**	2.36	KAZ	1.012	1.452	NEW	3.131	20.917**
LIT	8.046**	17.389**	KOR	3.997	2.158	PHI	2.288	23.325**
POR	1.207	1.099	LAT	3.106	1.782	POR	0.299	3.965
ROM	6.013**	25.707**	LEB	20.025**	13.251**	ROM	7.913**	14.827**
RUS	5.234	3.527	LIT	1.281	1.195	RUS	4.911	5.197
SLO	23.018**	11.021**	PER	15.229**	10.274**	SLO	1.584	5.316
SLV	16.930**	11.091**	POR	1.75	3.147	SPA	34.025**	23.275**
TUR	25.842**	3.069	ROM	0.342	14.713**	THA	8.532**	2.319
UKR	26.953**	15.777**	RUS	4.645	3.339	URU	10.680**	27.283**
URU	18.040**	7.068**	SLO	17.535**	2.618	VEN	1.067	27.330**
VEN	39.322**	14.204**	SPA	3.463	14.422**			
			TUR	3.492	2.068			
			UKR	38.537**	13.593**			
			URU	0.001	6.533**			
			VEN	1.234	0.121			
S_T^S	48.198**	28.797**	S_T^S	38.537**	17.505**	S_T^S	42.834**	27.330**

Table notes. The poolability test statistics for individual countries are reported in the row adjacent to their country identifier and below the dependent variable indicating the regressand in the relevant two variable system of equations to which the results refer. The individual country poolability test statistics have a chi-square distribution with k (=2 in this case) degrees of freedom giving a 5% critical value for all of these tests is 5.99. S_T^S denotes the maximum poolability test statistic (by column) which have 5% critical values with (k =) 2 slope coefficients of 11.948 (N=20), 12.328 (N=25) and 12.785 (N=30) - see Table 1 in Kapetanios (2003, p. 14). In our applications with N = 24, N = 28 and N = 23 the approximate 5% critical values for S(sup) are: 12.252, 12.602 and 12.176, respectively. Rejection of poolability is indicated by **.

Table 3: Individual country time-series ordered probit regressions for Fitch and Moody's: lag length selection

Country	SC ΔRF_{it}				ΔRF_{it}	SC ΔRM_{it}				ΔRM_{it}
	1 lag	2 lags	3 lags	4 lags	Obs	1 lag	2 lags	3 lags	4 lags	Obs
ARG	0.53631*	0.58403	0.61612	0.67089	171	0.69838*	0.72917	0.76953	0.82635	171
BAR	0.61508*	0.68566	NA	NA	140	0.50112*	0.55415	0.62548	0.69680	138
BRA	0.59614*	0.64056	0.68673	0.72706	200	0.52037*	0.54488	0.56736	0.61970	200
CYP	0.47042*	0.55237	NA	NA	116	0.58523*	0.61602	0.64732	0.71365	114
DOM	0.87299*	0.97705	0.98537	1.09593	79	0.78592*	0.82560	0.89203	1.00197	78
ECU	0.68947*	0.77783	0.86647	0.95469	105	0.90998*	0.99830	1.05972	1.14798	105
GRE	0.81902*	0.84689	0.89770	0.93620	189	0.70162	0.66667*	0.72066	0.77080	189
HUN	0.44597*	0.50265	0.55933	0.60525	184	0.72203*	0.77872	0.83540	0.88054	184
ICE	0.44768*	NA	NA	NA	141	0.58413*	0.60553	0.66121	NA	139
INO	0.64515*	NA	NA	NA	173	0.69737*	0.72923	0.78862	0.84760	170
IRE	0.45551*	0.49211	0.53797	0.58041	202	0.54723*	0.58540	0.62965	0.64633	202
ITA	0.29891*	0.35010	NA	NA	206	0.27408*	0.32580	NA	NA	206
JAM	0.84802*	0.98443	1.12083	1.12352	60	0.83714*	0.97186	1.10657	NA	61
LAT	0.59133*	0.66952	0.73698	0.81562	122	0.53604*	0.59449	0.64696	0.72579	121
LIT	0.45215*	0.49418	0.55009	0.59491	175	0.51556*	0.57457	0.63357	0.67604	175
POR	0.45429*	0.49959	0.53860	0.54338	204	0.48344*	0.53330	0.48897	NA	205
ROM	0.71578*	0.78053	0.81798	NA	153	0.60354*	0.62970	0.69537	0.71938	150
RUS	0.84075*	0.89348	0.94102	0.99195	177	0.63708*	0.67876	0.72920	0.78721	177
SLO	0.47559*	0.53277	0.58993	0.61666	180	0.45066*	0.50812	0.56556	0.61019	180
SLV	0.39000*	0.44656	0.50312	NA	184	0.44660*	0.50303	NA	NA	185
TUR	0.62499*	0.67712	0.72925	0.77500	204	0.24508*	0.29680	NA	NA	206
UKR	0.63845*	0.71985	0.80126	0.86210	117	0.35462*	0.43494	NA	NA	119
URU	0.75347*	0.78548	0.81833	0.86819	199	0.49599*	0.51549	0.55529	0.60188	199
VEN	0.63891*	0.70020	0.76149	0.80679	167	0.47915*	0.51456	0.56127	0.61479	167

SC ΔRF_{it} indicates the SC where ΔRF_{it} is the dependent variable while SC ΔRM_{it} indicates the SC where ΔRM_{it} is the dependent variable. All models are estimated over the sample period to ensure the reported SC statistics are comparable. An asterisk indicates the minimized SC for each country. Not all models could be estimated at all lag lengths (models that could not be estimated are indicated with an entry of NA). Obs represents the sample size.

Table 4: Individual country time-series ordered probit regressions for Fitch and S&P's: lag length selection

Country	SC ΔRF_{it}				ΔRF_{it}	SC ΔRS_{it}				ΔRS_{it}
	1 lag	2 lags	3 lags	4 lags	Obs	1 lag	2 lags	3 lags	4 lags	Obs
ARG	0.54681*	0.60107	0.62482	0.68272	171	0.75220*	0.78088	0.82736	0.88072	171
BRA	0.58967*	0.64235	0.68319	0.72584	200	0.54333*	0.59562	0.64828	0.70039	200
CYP	0.47560*	0.50175	NA	NA	116	0.55828*	NA	NA	NA	117
CZE	0.33545*	0.39015	0.44484	0.49953	192	0.33220*	0.38694	0.44169	0.49643	192
DOM	0.59584*	0.68999	0.78405	0.87749	96	0.80711*	0.84883	0.89715	0.98061	96
ECU	0.66290*	0.75147	0.74522	0.83378	105	1.05216*	1.14076	1.22305	1.31149	105
EST	0.57329*	0.63348	0.69563	0.75723	164	0.46763*	0.52697	0.57554	NA	165
GRE	0.79813*	0.81703	0.85879	0.90476	189	0.77174*	0.82507	0.87327	0.92043	189
HOG	0.31924*	0.37128	0.42332	0.45910	204	0.41481*	0.46664	0.51847	0.57029	204
ICE	0.45944*	NA	NA	NA	141	0.51406*	0.57616	NA	NA	140
INO	0.62273*	0.68144	0.73315	0.78832	170	1.22717*	1.25612	1.31064	1.36729	170
IRE	0.39194*	0.42660	0.47341	0.52391	202	0.57165*	0.58591	0.60552	0.63559	202
JAM	0.73201*	0.86721	0.91571	1.02790	60	0.83771*	0.97411	0.97036	1.02579	60
KAZ	0.52840*	0.58702	0.64563	0.66262	176	0.56652*	0.62462	0.68316	0.74169	176
KOR	0.77410*	0.80169	0.83129	0.88445	182	0.96934*	1.00507	1.01624	1.07343	182
LAT	0.53285*	0.58292	0.59471	0.65738	158	0.62765*	0.67834	0.72817	0.75190	158
LEB	0.41491*	0.47416	0.50574	0.56497	174	0.46246*	0.52172	0.58099	0.64026	174
LIT	0.54771*	0.58721	0.64679	0.70248	170	0.50674*	0.55075	0.59351	0.65269	170
PER	0.47935*	0.54890	0.59854	0.66825	142	0.47935*	0.54890	0.54509	0.61483	142
POR	0.46042*	0.50578	0.54429	0.58921	204	0.43895*	0.48870	0.52798	0.56198	204
ROM	0.74054	0.70387*	0.72827	0.77850	172	0.64904*	0.70887	0.76871	0.82352	172
RUS	0.83838*	0.88495	0.93766	0.99143	178	0.86705*	0.89139	0.94256	0.96443	178
SLO	0.47116*	0.52758	NA	NA	182	0.46539*	0.48107	0.51858	0.54824	180
SPA	0.34437*	0.39648	0.44861	0.50075	204	0.36748*	0.41962	0.47175	0.52389	204
TUR	0.59518*	0.63955	0.69034	0.71128	204	0.47050*	0.50365	0.54760	0.59062	204
UKR	0.64274*	0.70942	0.79138	0.79116	116	0.83098*	0.90146	0.98342	1.01894	116
URU	0.73615*	0.77670	0.77309	0.82106	199	0.79612*	0.81128	0.82348	0.84684	199
VEN	0.62727*	0.68855	0.74094	0.79133	167	0.77391*	0.79104	0.82443	0.82659	167

SC ΔRF_{it} indicates the SC where ΔRF_{it} is the dependent variable while SC ΔRS_{it} indicates the SC where ΔRS_{it} is the dependent variable. All models are estimated over the sample period to ensure the reported SC statistics are comparable. An asterisk indicates the minimized SC for each country. Not all models could be estimated at all lag lengths (models that could not be estimated are indicated with an entry of NA). Obs represents the sample size.

Table 5: Individual country time-series ordered probit regressions for Moody's and S&P's: lag length selection

Country	SC ΔRM_{it} 1 lag	SC ΔRM_{it} 2 lags	SC ΔRM_{it} 3 lags	SC ΔRM_{it} 4 lags	ΔRM_{it} Obs	SC ΔRS_{it} 1 lag	SC ΔRS_{it} 2 lags	SC ΔRS_{it} 3 lags	SC ΔRS_{it} 4 lags	ΔRS_{it} Obs
ARG	0.56782*	0.60118	0.63433	0.68366	216	0.62817*	0.66530	0.70784	0.75183	216
BAR	0.52769*	0.61373	0.66313	0.74892	109	0.51622*	NA	NA	NA	112
BRA	0.50931*	0.56181	0.60581	0.65803	201	0.55038*	0.60273	0.64856	0.66881	201
CYP	0.41970*	0.48085	0.51789	NA	164	0.49317*	0.55227	0.53751	0.56816	163
DOM	0.67460*	0.74217	0.81238	0.89682	105	0.89819*	0.94108	1.02848	1.07199	106
ECU	0.72561*	0.79811	0.84186	0.88331	133	0.92543*	0.99860	1.07213	1.14565	133
GRE	0.63474*	0.64058	0.67534	0.72252	207	0.74927*	0.78954	0.82425	0.84524	207
ICE	0.47402*	0.51115	0.53809	0.58522	224	0.41182*	0.45824	0.50654	0.54981	224
INO	0.57715*	0.61840	0.66695	0.71584	209	1.10683*	1.11525	1.16305	1.21110	209
IRE	0.42951*	0.45268	0.48009	0.50403	261	0.46913*	0.48974	0.48560	0.50159	261
JAM	0.43236*	0.50167	0.52275	0.57915	141	0.60123*	0.65421	0.65212	0.71510	141
LAT	0.54053	0.54215	0.53629*	0.61533	121	0.70925*	0.78730	0.85190	0.90699	122
LIT	0.50972*	0.57011	0.63013	0.68872	170	0.52041*	0.57320	0.59489	0.65505	170
NEW	0.24892*	0.28694	0.32422	0.36221	300	0.23616*	0.26058	0.29841	0.33643	300
PHI	0.40156*	0.45110	0.48048	0.52994	217	0.34948*	0.39907	0.44865	0.49823	217
POR	0.44783*	0.49588	0.53011	0.55498	224	0.45172*	0.49968	0.54798	0.59619	224
ROM	0.61449*	0.66895	NA	NA	154	0.60568*	0.64572	0.71028	0.76287	151
RUS	0.68779*	0.72678	0.77691	0.83430	177	0.87363*	0.92397	0.94004	0.98820	177
SLO	0.39682*	0.44887	0.50295	0.55687	195	0.53823*	0.58843	0.64236	0.69574	195
SPA	0.28345*	0.32417	0.36490	0.40563	276	0.28706*	0.32779	0.36852	0.40925	276
THA	0.28631*	0.31416	0.32689	0.36707	264	0.35030*	0.38382	0.41370	0.45556	264
URU	0.47195*	0.50581	0.51274	0.56188	210	0.79877*	0.83630	0.87651	0.91617	210
VEN	0.34405*	0.36820	0.40531	0.44054	290	0.73986*	0.75546	0.78384	0.79913	290

SC ΔRM_{it} indicates the SC where ΔRM_{it} is the dependent variable while SC ΔRS_{it} indicates the SC where ΔRS_{it} is the dependent variable. All models are estimated over the sample period to ensure the reported SC statistics are comparable. An asterisk indicates the minimized SC for each country. Not all models could be estimated at all lag lengths (models that could not be estimated are indicated with an entry of NA). Obs represents the sample size.

Table 6: Individual country time-series ordered probit regressions for Fitch and Moody's

	ΔRM_{it-1} to ΔRF_{it}		ΔRF_{it-1} to ΔRF_{it}		ΔRF_{it-1} to ΔRM_{it}		ΔRM_{it-1} to ΔRM_{it}		Observations	
Country	GNC	P[t]	Habit	P[t]	GNC	P[t]	Habit	P[t]	Dep ΔRF_{it}	Dep ΔRM_{it}
ARG	0.563***	0.010	0.292**	0.012	0.353*	0.079	0.110	0.642	174	174
BAR	-0.035	0.664	-0.007	0.803	-0.019	0.773	-0.090	0.382	141	141
BRA	-0.107	0.244	-0.086	0.283	-0.104	0.259	-0.130	0.217	203	203
CYP	0.787**	0.018	-0.077	0.400	-0.023	0.662	-0.023	0.668	117	117
DOM	0.811	0.109	-0.059	0.412	-0.004	0.960	-0.017	0.988	82	81
ECU	0.642	0.133	-0.404	0.184	-0.380	0.186	0.613	0.141	108	108
GRE	0.417*	0.077	-0.178	0.146	0.310	0.257	0.243	0.317	192	192
HUN	0.000	0.716	-0.000	0.968	0.000	0.636	0.000	0.721	187	187
ICE	-0.570*	0.084	1.136***	0.010	0.943**	0.022	-0.385*	0.077	141	141
INO	0.427	0.427	0.369	0.588	0.169	0.789	0.245	0.652	173	173
IRE	-0.032	0.521	-0.068	0.395	-0.048	0.430	-0.022	0.543	205	205
ITA	1.122**	0.035	-1.368**	0.022	0.067	0.612	-0.007	0.842	207	207
JAM	-0.088	0.613	0.029	0.729	0.029	0.729	-0.088	0.613	63	63
LAT	-0.241	0.254	1.145*	0.074	1.190**	0.040	-0.254	0.213	128	127
LIT	2.003***	0.001	-0.388	0.197	-0.030	0.625	-0.037	0.465	178	178
POR	0.577*	0.072	0.501	0.190	0.433*	0.082	0.259	0.129	207	207
ROM	0.523*	0.098	-0.044	0.499	0.033	0.558	-0.730***	0.007	157	156
RUS	0.342	0.302	0.527***	0.000	0.830***	0.001	-0.112	0.515	180	180
SLO	-0.089	0.281	-0.210	0.172	-0.160	0.262	-0.066	0.353	183	183
SLV	-0.074	0.391	-0.123	0.340	-0.038	0.670	-0.023	0.676	186	186
TUR	-0.029	0.660	-0.022	0.573	1.078***	0.008	-0.010	0.899	207	207
UKR	-0.021	0.718	-0.009	0.788	-0.019	0.749	-0.044	0.601	120	120
URU	-0.131	0.226	0.339*	0.072	0.064	0.569	0.625**	0.048	202	202
VEN	-0.018	0.720	0.004	0.852	0.018	0.821	-0.079	0.390	170	170

GNC denotes the Granger causality (herding) coefficient and Habit represents the autoregressive (habit) coefficient. P[t] gives the probability value of a t-test for the significance of the corresponding coefficient based upon Huber White (QML) robust coefficient standard errors. Dep ΔRX_{it} indicates that ΔRX_{it} is the dependent variable where, X = F, M or S. ΔRX_{it-1} to ΔRY_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRY_{it} is the dependent variable, where, Y = F, M or S. Similarly, ΔRX_{it-1} to ΔRX_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRX_{it} is the dependent variable. *, ** and *** denote rejection of the null hypothesis that a statistic is zero at the 10%, 5% and 1% levels, respectively. Observations give the number of time-series observations used to estimate a model. There are results for (N =) 24 countries and the total number of observations (summing across all 24 countries) is 3911 with ΔRF_{it} as the dependent variable and 3908 with ΔRM_{it} as the dependent variable.

Table 7: Individual country time-series ordered probit regressions for Fitch and S&P's

Country	ΔRS_{it-1} to ΔRF_{it} GNC	P[t]	ΔRF_{it-1} to ΔRF_{it} Habit	P[t]	ΔRF_{it-1} to ΔRS_{it} GNC	P[t]	ΔRS_{it-1} to ΔRS_{it} Habit	P[t]	Observations Dep ΔRF_{it}	Dep ΔRS_{it}
ARG	0.023	0.874	0.463**	0.013	0.543*	0.051	0.219	0.244	174	174
BRA	0.663	0.196	-0.273	0.142	0.761	0.179	-0.416**	0.045	203	203
CYP	1.312**	0.031	-0.015	0.834	-0.081	0.245	-0.167	0.295	117	117
CZE	-0.081	0.356	-0.100	0.445	-0.100	0.445	-0.081	0.356	195	195
DOM	1.057***	0.000	-0.002	0.895	0.480*	0.064	-0.000	1.000	99	99
ECU	0.597**	0.034	-0.148*	0.056	-0.101	0.131	0.425**	0.036	108	108
EST	0.910	0.113	-0.063	0.413	0.893*	0.092	-0.117	0.302	167	167
GRE	0.718***	0.005	-0.262*	0.095	0.629**	0.035	0.086	0.701	192	192
HOG	-0.144	0.344	-0.100	0.445	1.403**	0.042	-0.226	0.149	207	207
ICE	-0.592	0.373	1.105**	0.045	1.215***	0.001	-0.099	0.817	141	141
INO	0.485***	0.001	0.616***	0.001	1.011***	0.001	-0.082	0.653	173	173
IRE	1.616***	0.000	-0.068	0.428	0.503	0.169	-0.041	0.461	205	205
JAM	1.519***	0.001	-0.355*	0.061	-0.029	0.659	-0.021	0.838	63	63
KAZ	0.819	0.138	-0.101	0.318	0.756	0.164	-0.119	0.264	179	179
KOR	0.185	0.197	-0.125	0.715	0.011	0.968	0.075	0.667	185	185
LAT	0.515	0.121	0.722*	0.084	0.648	0.111	0.453	0.145	161	161
LEB	-0.043	0.646	-0.076	0.428	-0.051	0.489	-0.029	0.664	177	177
LIT	1.009*	0.096	-0.168	0.238	0.957*	0.091	-0.160	0.331	173	173
PER	-0.161	0.294	-0.161	0.294	-0.161	0.294	-0.161	0.294	145	145
POR	0.860**	0.037	0.354	0.304	0.232	0.334	0.564**	0.048	207	207
ROM	0.625	0.169	-0.030	0.558	-0.023	0.585	-0.024	0.637	175	175
RUS	0.180	0.430	0.525***	0.000	0.774***	0.000	0.158	0.259	181	181
SLO	-0.249	0.128	-0.249	0.128	0.895	0.134	-0.225	0.155	183	183
SPA	1.537**	0.012	-0.445*	0.078	-0.008	0.817	-0.012	0.787	207	207
TUR	1.315***	0.005	-0.216	0.124	0.443	0.284	0.893	0.143	207	207
UKR	-0.004	0.873	-0.007	0.814	-0.013	0.782	-0.007	0.865	119	119
URU	0.516	0.217	0.047	0.911	0.793***	0.001	-0.543***	0.008	202	202
VEN	0.306*	0.063	-0.005	0.822	0.472	0.187	0.000	1.000	170	170

GNC denotes the Granger causality (herding) coefficient and Habit represents the autoregressive (habit) coefficient. P[t] gives the probability value of a t-test for the significance of the corresponding coefficient based upon Huber White (QML) robust coefficient standard errors. Dep ΔRX_{it} indicates that ΔRX_{it} is the dependent variable where, X = F, M or S. ΔRX_{it-1} to ΔRY_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRY_{it} is the dependent variable, where, Y = F, M or S. Similarly, ΔRX_{it-1} to ΔRX_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRX_{it} is the dependent variable. *, ** and *** denote rejection of the null hypothesis that a statistic is zero at the 10%, 5% and 1% levels, respectively. Observations give the number of time-series observations used to estimate a model. There are results for (N =) 28 countries and the total number of observations (summing across all 28 countries) is 4715 with both ΔRF_{it} and ΔRS_{it} as the dependent variable.

Table 8: Individual country time-series ordered probit regressions for Moody's and S&P's

Country	ΔRS_{it-1} to ΔRM_{it} GNC	P[t]	ΔRM_{it-1} to ΔRM_{it} Habit	P[t]	ΔRM_{it-1} to ΔRS_{it} GNC	P[t]	ΔRS_{it-1} to ΔRS_{it} Habit	P[t]	Observations Dep ΔRM_{it}	Dep ΔRS_{it}
ARG	0.509**	0.012	0.156	0.599	0.800**	0.034	0.246	0.291	219	219
BAR	0.045	0.601	-0.058	0.582	0.058	0.582	-0.045	0.601	112	112
BRA	0.764	0.186	-0.239	0.104	-0.141	0.195	-0.158	0.155	204	204
CYP	1.203*	0.056	-0.202	0.260	0.767**	0.042	-0.540	0.115	166	166
DOM	0.265	0.175	-0.082	0.911	-0.326	0.612	0.012	0.738	108	109
ECU	0.609**	0.032	0.160	0.412	0.075	0.572	0.410**	0.035	136	136
GRE	0.636***	0.009	-0.004	0.979	-0.041	0.849	0.425	0.204	210	210
ICE	1.979***	0.000	-0.488**	0.020	-0.077	0.756	1.468***	0.002	227	227
INO	0.338**	0.030	0.310	0.239	0.951***	0.000	-0.009	0.970	212	212
IRE	1.569***	0.000	-0.176	0.147	0.230	0.255	-0.104	0.247	264	264
JAM	1.614***	0.000	-0.859***	0.009	-0.064	0.476	0.005	0.916	144	144
LAT	0.948*	0.075	-0.096	0.461	0.381	0.259	0.715	0.181	127	128
LIT	1.137*	0.065	-0.047	0.388	-0.017	0.712	-0.009	0.788	173	173
NEW	1.595***	0.005	-0.078	0.422	0.032	0.664	-0.015	0.749	303	303
PHI	1.622**	0.021	-0.294	0.272	-0.007	0.824	-0.014	0.761	220	220
POR	0.638**	0.011	0.135	0.261	0.124	0.307	0.625**	0.016	227	227
ROM	0.960***	0.004	-0.771***	0.004	-0.607*	0.066	-0.000	1.000	156	157
RUS	0.301	0.167	0.315	0.231	0.970***	0.000	0.342*	0.082	180	180
SLO	1.068**	0.017	-0.068	0.414	0.689***	0.000	0.714**	0.029	198	198
SPA	-0.025	0.782	-0.033	0.647	-0.013	0.736	-0.010	0.811	279	279
THA	2.150***	0.004	1.279**	0.027	0.650	0.315	0.875	0.199	267	267
URU	0.248	0.125	0.539**	0.041	0.001	0.961	-0.002	0.872	213	213
VEN	0.520***	0.008	-0.064	0.410	-0.007	0.732	-0.001	0.838	293	293

GNC denotes the Granger causality (herding) coefficient and Habit represents the autoregressive (habit) coefficient. P[t] gives the probability value of a t-test for the significance of the corresponding coefficient based upon Huber White (QML) robust coefficient standard errors. Dep ΔRX_{it} indicates that ΔRX_{it} is the dependent variable where, X = F, M or S. ΔRX_{it-1} to ΔRY_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRY_{it} is the dependent variable, where, Y = F, M or S. Similarly, ΔRX_{it-1} to ΔRX_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRX_{it} is the dependent variable. *, ** and *** denote rejection of the null hypothesis that a statistic is zero at the 10%, 5% and 1% levels, respectively. Observations give the number of time-series observations used to estimate a model. There are results for (N =) 23 countries and the total number of observations (summing across all 23 countries) is 4638 with ΔRM_{it} as the dependent variable and 4641 with ΔRS_{it} as the dependent variable.

Table 9: Summary of CRA leadership based on ordered probit results

CRA pairing→	Fitch and Moody's			Fitch and S&P's			Moody's and S&P's		
CRA leader→ Country ↓	Fitch	Moody's	Dual	Fitch	S&P's	Dual	Moody's	S&P's	Dual
ARG		L							L, M
BAR				-	-	-			
BRA									
CYP		L			L		L		
CZE	-	-	-				-	-	-
DOM					L				
ECU					L, HS			L, HS	
EST	-	-	-				-	-	-
GRE						L, S		L	
HOG	-	-	-	L			-	-	-
HUN				-	-	-	-	-	-
ICE	L, HF			L, HF				L, HS, CM	
INO						L, F, HF			L, M
IRE					L			L	
ITA		L, CF		-	-	-	-	-	-
JAM					L			L, CM	
KAZ	-	-	-				-	-	-
KOR	-	-	-				-	-	-
LAT	L								
LEB	-	-	-				-	-	-
LIT		L							
NEW	-	-	-					L	
PER	-	-	-				-	-	-
PHI	-	-	-					L	
POR	L				L, HS			L, HS	
ROM								L, CM	
RUS	L, HF			L, HF			L		
SLO									L, S, HS

Table 9 (continued): Summary of CRA leadership based on ordered probit results

CRA pairing→	Fitch and Moody's			Fitch and S&P's			Moody's and S&P's		
CRA leader→ / Country ↓	Fitch	Moody's	Dual	Fitch	S&P's	Dual	Moody's	S&P's	Dual
SLV				-	-	-	-	-	-
SPA	-	-	-		L				
THA	-	-	-					L, HM	
TUR	L				L		-	-	-
UKR							-	-	-
URU				L, CS					
VEN								L	

The pair of CRAs results under consideration is specified in the row labeled "CRA pairing". If an CRA unambiguously leads the other for any pairing for a particular country this is indicated with the letter "L" in that CRA's column. If there is bi-directional Granger-causality (dual leadership) this is indicated with an "L" in the column headed "Dual". The CRA with the largest GNC coefficient when there is bi-directional Granger-causality is indicated with the symbol "F" (Fitch), "M" (Moody's) or "S" S&P's in the "Dual" column. The absence of leadership is indicated by a blank entry while "-" indicates that tests could not be conducted for a particular CRA pairing in a specific country. When an CRA's leadership is confirmed by it exhibiting positive habit behaviour this is indicated by "H*", where * denotes F for Fitch, M for Moody's and S for S&P's. Leadership that is reinforced by contrarian habit behaviour is denoted with "C*".

Table 10: Time-series GNC Tests with structural change in 2007 M06 (ordered probit regression)

Country	GNC-pre	P[t(h)]	GNC-post	P[t(h)]	P(break)	Obs	GNC-pre	P[t(h)]	GNC-post	P[t(h)]	P(break)	Obs
			ΔRM_{it-1} to ΔRF_{it}						ΔRF_{it-1} to ΔRM_{it}			
BAR	-0.031	0.667	-0.061	0.679	0.710	141	-0.052	0.534	0.008	0.922	0.632	141
ECU	0.139	0.532	0.695	0.126	0.155	108	0.028	0.791	-0.490	0.173	0.159	108
GRE	0.100	0.173	0.467*	0.073	0.075*	192	0.313*	0.087	0.310	0.293	0.990	192
IRE	0.045	0.781	-0.047	0.396	0.605	205	-0.110	0.485	-0.034	0.540	0.580	205
LAT	0.080	0.201	-0.874*	0.052	0.047**	128	0.386	0.190	1.449**	0.016	0.019**	127
LIT	2.277***	0.000	0.986**	0.045	0.021**	178	-0.046	0.538	0.018	0.854	0.631	178
POR	2.727***	0.000	0.399*	0.093	0.002***	207	0.425*	0.090	0.433*	0.089	0.968	207
UKR	-0.016	0.729	-0.047	0.734	0.749	120	-0.044	0.648	-0.000	0.998	0.709	120
			ΔRS_{it-1} to ΔRF_{it}						ΔRF_{it-1} to ΔRS_{it}			
ECU	0.267	0.166	0.606**	0.036	0.143	108	0.059	0.577	-0.128	0.136	0.178	108
EST	0.479	0.207	0.987	0.125	0.214	167	0.253	0.412	1.021	0.100	0.098*	167
GRE	0.604*	0.083	0.758***	0.009	0.694	192	1.054**	0.024	0.545*	0.052	0.289	192
IRE	0.551**	0.047	1.781***	0.000	0.001***	205	0.230	0.432	0.510	0.168	0.131	205
KAZ	0.921	0.119	0.325	0.308	0.129	179	0.265	0.309	1.571**	0.034	0.032**	179
LAT	0.614	0.197	0.589	0.121	0.951	161	0.549	0.227	0.625	0.126	0.840	161
LIT	0.414	0.165	1.724**	0.032	0.041**	173	1.114*	0.075	0.360	0.179	0.101	173
POR	0.310	0.333	0.930**	0.050	0.184	207	0.611**	0.014	0.190	0.463	0.180	207
RUS	0.175	0.455	0.344**	0.011	0.414	181	0.783***	0.000	0.460*	0.058	0.233	181
SPA	0.536*	0.092	2.015***	0.003	0.006***	207	-0.012	0.831	-0.005	0.885	0.908	207
UKR	0.011	0.810	-0.010	0.782	0.758	119	-0.025	0.687	0.004	0.952	0.730	119
VEN	0.307*	0.064	0.147	0.374	0.343	170	0.486	0.184	0.239	0.330	0.326	170
			ΔRS_{it-1} to ΔRM_{it}						ΔRM_{it-1} to ΔRS_{it}			
BAR	0.061	0.716	0.042	0.601	0.885	112	0.060	0.575	0.048	0.764	0.933	112
CYP	-0.031	0.872	1.463**	0.035	0.034**	166	0.498	0.169	0.773**	0.044	0.479	166
DOM	0.277	0.163	0.074	0.937	0.830	108	-0.399	0.595	-0.141	0.557	0.629	109
ECU	0.215	0.262	0.637**	0.036	0.188	136	0.314*	0.079	0.049	0.721	0.154	136
GRE	0.302**	0.032	0.738**	0.010	0.077*	210	0.179	0.121	-0.114	0.684	0.354	210
IRE	0.730**	0.021	1.691***	0.000	0.005***	264	0.047	0.578	0.236	0.254	0.222	264
LAT	0.489	0.184	1.118**	0.048	0.092*	127	0.174	0.336	0.605	0.308	0.453	128
LIT	0.539	0.151	1.694**	0.026	0.039**	173	-0.015	0.712	-0.031	0.735	0.776	173
POR	0.283	0.130	0.756***	0.005	0.030**	227	0.479**	0.020	0.032	0.725	0.029**	227
SPA	-0.041	0.723	-0.003	0.975	0.762	279	-0.008	0.851	-0.019	0.701	0.833	279

GNC-pre and GNC-post denote the Granger causality (herding) coefficient before and after the break point, respectively. P[t(h)] gives the probability value of a t-test for the significance of the adjacent coefficient and P(break) is the probability value of a t-test for the significance of a break between 2007M05 and 2007M06; both p-values are based upon Huber White (QML) robust coefficient standard errors. ΔRX_{it-1} to ΔRY_{it} indicates a statistic referring to the coefficient on ΔRX_{it-1} in the equation where ΔRY_{it} is the dependent variable, where X = F, M or S and Y = F, M or S. Obs represents the number of observations used in estimation. *, ** and *** denote rejection of the null at the 10%, 5% and 1% levels, respectively. Omitted results for countries are due to an inability to obtain (satisfactory) estimates.

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