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Information Propagation in Financial Markets

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by

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Abstract

This dissertation consists of three essays which examine information flows through financial markets and across firms, and investigates the factors affecting the process of information dissemination. The first essay examines whether the announcement of a credit rating change for a given firm contains information pertinent to the valuations of intra-industry peer firms. I identify an information spillover effect on peer firms surrounding credit rating downgrades. Further, I find that the post-announcement spillover effects are indicative of an overreaction in the market's response to the downgrade announcement. Peer firms exhibit predictability in their post-announcement returns as a function of their relative transparency.

The second essay explores the relation between instances of credit rating initiations and stock market liquidity. Traditional finance literature holds the view that liquidity is impaired as a function of information asymmetry. Additionally, that credit ratings have been shown to reduce information asymmetry. This study uses instances of new credit ratings to examine the change in stock market liquidity surrounding the announcement of the new rating. My results suggest that rating initiations improve in the liquidity of the newly rated firm's equity and that managers exploit this price support through seasoned equity offerings.

The third essay investigates information flows through the social networks of board members. I find that the degree to which a CEO and her directors overlap in social communities affects the governance of the firm and that these effects are conditional upon the adverse reputation costs faced by the board. For firms whose boards face relatively lower (higher) potential adverse reputation costs to bad behavior, clustering is associated with poorer (better) governance and greater (lesser) expropriation by managers.

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In addition to my academic debts, I owe a great deal to those who supported me personally in developing this body of knowledge. My wife, Crystal, has been a source of unyielding support and provision during this arduous process. My daughters, Greenlee and Leland June, never withheld their love and encouragement even when the workload necessitated my temporary absence. My family for their support and understanding. And, to my cherished friends who were always there to keep me grounded.

Dedication

For Crystal, Greenlee, and Leland June.

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I. Introduction

The efficacy of managers and the price setting mechanisms of financial markets are, ultimately, reliant upon the transfer and assimilation of information. Information fidelity is paramount to the functioning of efficient financial markets and to the effectiveness of firm managers. The three essays in this dissertation examine information flows through financial markets and across firms and investigate the factors affecting the processes of information dissemination. What impediments affect information flows in financial markets? Under what circumstances will restrictions on the flow of information cause price deviations from intrinsic values? How can individuals or firms mitigate the problems associated with restrictions in the transfer of information?

In the first essay, I examine the spillover effects of credit ratings changes on the intra-industry peers of the rated firm. To the extent that credit ratings contain information about the industry in which the firm operates, changes in the rating of a given firm should have valuation consequences for like firms. I analyze both the contemporaneous and long-term valuation impacts on peer firms and identify an information spillover effect on peer firms surrounding credit rating downgrades. The equity values of peer firms suffer, on average, at the announcement of an intra-industry downgrade. Furthermore, the post-announcement spillover effects are indicative of an overreaction in the market's response to the downgrade announcement. Peer firms exhibit predictability in their equity returns post-announcement as a function of their relative transparency. Information induced overreaction seems to be present at the announcement of an intra-industry credit downgrade.

The second essay builds on prior literature that examines the correlation between equity liquidity and credit ratings. Traditional finance literature holds the view that liquidity is impaired as a function of information asymmetry. Additionally, credit ratings have been shown to reduce information asymmetry. Using instances of new, long-term issuer credit rating initiations, I examine contemporaneous movements in stock market liquidity surrounding the announcement of the new credit rating. Controlling for contemporaneous changes in market/industry-wide liquidity by propensity matching firms who obtain a rating with those who do not, my findings show that credit rating initiations are associated with statistically significant increases in the liquidity of a firm's equity. Additionally, managers capitalize on this price support through increased seasoned equity offering activity.

While my research primarily focuses on information propagation in financial markets, I also investigate information flows through networks of individuals. Using BoardEx, an extensive database which covers the social networks of business executives, I investigate the effects that networks impart upon firm governance. I identify "social clustering" (roughly defined as close-knit communities within a network) and study its effects on the information environment of firms and on the incentives, behaviors, and outcomes of network participants. The degree to which a CEO and her directors overlap in social communities affects the governance of the firm and that these effects are conditional upon the adverse reputation costs faced by the board. For firms whose boards face relatively lower (higher) potential adverse reputation costs to bad behavior, clustering is associated with poorer (better) governance and greater (lesser) expropriation by firm managers.

II. Essay 1: Spillover Valuation Effects of Credit Rating Changes: *'Shoot First, Ask Questions Later'*[1]

Wayne Y. Lee and Garrett A. McBrayer

A. Abstract

Opacity hinders information efficiency. When information is asymmetric, investors use credit downgrades to infer adverse changes in the creditworthiness of similar firms in the same industry. Intra-industry cumulative abnormal equity returns (*CARs)* over the seven-day event window around announcements of rating downgrades from investment to speculative grade average -1.23%, and -1.30%, controlling for rating, firm characteristics, as well as year and industry fixed effects. Overreaction results when price contagion is dominated by noise trading. *CAR*s over three, six, and twelve-month windows starting four days after downgrade announcements average 1.45%, 5.02%, and 5.47%, respectively. The reversals in price declines are predominantly on shares of transparent industry peers. For opaque peers, share price declines continue post announcement. Significant average increases in the return on assets, profit margin, and earnings per share of industry peers from the preceding to subsequent fiscal year around downgrade announcement years corroborate the post announcement rise in share prices. Lastly, we show that transparency is priced. Transparent firms have lower systematic risks and lower costs of capital.

JEL Classification: G14, G24

Keywords: contagion, market efficiency, credit ratings, opacity

[1] We thank seminar participants at the University of Arkansas and the 2015 Eastern Finance Association Annual meetings for their invaluable comments and suggestions. We thank especially Tim Yeager and Alexey Malakhov for their comments. All errors remain our own.

B. Introduction

Credit rating agencies play critical roles in alleviating informational asymmetries between borrowers and lenders and apportioning risks in financial markets. The value of the risk certification process depends on its objectivity, informativeness, and timeliness. Credibility is uncertain when issuers pay to be rated and can shop competing rating agencies. High regulatory costs of cheap talk and reputation considerations safeguard the trustworthiness of credit signals (Ottaviani and Sorensen, 2006). To assess creditworthiness, rating agencies count on their specialized access to non-public information about firms. Regulation Fair Disclosure Act (Reg FD) enacted in 2000 preserved the selective disclosures of private information by management to certified rating agencies.[2] The exclusion of equity analysts and other market participants from opportunities to obtain confidential information enhanced the informational advantage of ratings agencies. Following initial ratings, ratings agencies monitor firms for changes in creditworthiness and the threat of adverse rating changes motivates firms to take corrective actions (Boot, Milbourn, and Schmeits, 2006). Meetings with management (at least annually) are used to review past performance, discuss potential problems, and stay apprised of future plans. Explanations regarding ratings changes, as with initial ratings, refer only to public information to ensure the confidentiality of sensitive information provided by rated firms.

Public announcements of unexpected changes in credit ratings can convey latent but economically significant revisions in the private information that ratings agencies have about firms. Moreover, because ratings agencies recognize that risk management responses to ratings changes necessitate costly portfolio adjustments, ratings changes are more likely to anticipate longer term permanent rather than volatile market-driven changes in credit risk.

[2] Section 102(b)(2).

Performance based compensation and likelihood of dismissal induce managers to advance or voluntarily disclose good news, and delay or avoid the disclosure of bad news (Chen, Hong, and Stein, 2001). Market reactions to credit rating downgrades and upgrades are asymmetric. Holthausen and Leftwich (1986) find significant negative abnormal equity returns on one or more rating class credit downgrades of straight debt averaging -2.66% over a two-day window ending one day after announcement.[3] On credit upgrades, equity share price changes are positive, but are negligible and insignificant. Announcements of credit upgrades appear to be largely anticipated.

Jorion, Liu, and Shi (2005) examine the impact of Reg FD on the information content of credit rating changes. Their findings suggest the special exemption granted credit rating agencies to management disclosures of confidential information reduced the informativeness of prices. As Odders-White and Ready (2006) point out, firms more exposed to shocks initially observed by "insiders" will incur higher adverse selection costs that deters informed trading in equity. The rise and fall in equity share prices in reaction to credit rating upgrades and downgrades were larger and more significant post Reg FD. The exclusion of analysts and other market professionals had a greater impact on firms with more analysts as well as larger sized firms that were more likely to make use of selective disclosures to institutional investors.[4] Heflin, Subrahmanyam, and Zhang (2003) find, however, that voluntary disclosures by firms

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[3]For example, a change from A^+, A, A^- to BBB^+, BBB, or BBB^-. Holthausen and Leftwich (1986) do not find significant abnormal equity returns around announcements of credit downgrades within a rating class. Hand, Holthausen, and Leftwich (1992) also find that bond and stock prices react to unexpected additions of firms to the *S&P* Credit Watch List. In the three-day event window around the credit watch announcement, bonds decline relative to benchmark Treasuries by -1.39%, and CRSP equally-weighted market adjusted stock returns by -1.78%.

[4]The authors acknowledge the limitations of their event study. Sample period was confined to the 26 months prior and subsequent to the enactment of Reg FD on October 23, 2000 that coincided with an economic recession in 2001.

significantly increased post Reg FD and earnings forecast accuracy (actual from consensus) was relatively unchanged. A reduction in the adverse component of the bid-ask spread post Reg FD noted by Eleswarapu, Thompson, and Venkataraman (2004) points to improved information efficiency.

Observed drifts in equity share prices post credit downgrade announcements suggest that markets are not information efficient. When rated firms have the opportunity to take corrective actions, delays in credit downgrade announcements can mislead investors about the gravity of a firm's financial condition. Investors underestimate the longer-term real costs of financial distress associated with credit downgrades. Dichev and Piotroski (2001) find statistically significant negative abnormal equity returns of -10% to -14% in the first year, and an annualized -4% to -6% over the two and three years following credit ratings downgrades. The performance deficit is especially pronounced for firms with non-investment grade debt and small firms where analyst following and investor interest are low. A lack of transparency impedes investors' inferences.

This study focuses on the impact of long-term issuer credit ratings downgrades by Standard and Poor's (*S&P*) from investment-grade (>=*BBB*-) to speculative-grade (<=*BB*+) on similar firms in the same industry as credit-downgraded firms. Our motivation for examining these events stems, in part, from *S&P*'s literature on the information employed in determining credit ratings:

> "Credit ratings are *forward-looking opinions* about *credit risk*. Standard & Poor's credit ratings express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time. The reasons for ratings adjustments vary, and may be broadly related to overall shifts in the economy or business environment or more narrowly focused on circumstances affecting a specific industry, entity, or individual debt issue. The *likelihood of default* is the single most important factor in our assessment of creditworthiness." [5]

[5]http://www.standardandpoors.com/ratings/definitions-and-faqs/en/us.

To the extent credit rating agencies are better informed about business and financial risks, investors will use credit downgrade announcements to infer changes in the creditworthiness of similar firms within the same industry.[6] The unstructured and qualitative nature of the disclosures and differences in transparency make it difficult, however, for investors to discriminate across firms. We conjecture that when investors are asymmetrically informed, opacity exacerbates the variability in beliefs about an asset's fundamental value. Increased price uncertainty requires arbitrageurs to bear greater risk. The limits to informed arbitrage creates space for noise trading (Delong, Shleifer, Summers and Waldman, 1989 and 1990). An overreaction results when price contagion at credit downgrade announcements is dominated by noise trading. The resolution of information uncertainty and resumption of informed trading following credit downgrade announcements leads to price reversals. When investors are poorly informed, the market reaction at announcement is characterized by *'shoot first, ask questions later'*.

Our main findings can be briefly summarized as follows. First, we document significant negative intra-industry cumulative abnormal equity returns over the three-day to seven-day event windows around announcements of credit rating downgrades from investment to speculative grade. Intra-industry equity price declines are notably greater when the credit downgrades are unexpected, and only slightly smaller, the more severe is the competitive impairment of the credit downgraded firm.

Second, cumulative average abnormal equity returns on transparent industry peer firms

[6]Previously unknown future changes in business and financial risk factors may be implied in credit downgrade announcements. Business risk factors include country risk, industry condition, competitive position, business and geographic diversification, management, regulatory environment and strategy. Financial risk factors include capitalization, leverage, earnings, funding, liquidity, cash flow, risk management, and accounting. http://www.standardandpoors.com/aboutcreditratings/RatingsManualPrintGuide.html.

are less negative than on opaque industry peer firms. At best, however, a small percentage of transparent peer firms avoid a negative cumulative abnormal equity return at credit downgrade announcements. Investors overreact to potential adverse changes in the creditworthiness of similar firms in the same industry as credit-downgraded firms.

Third, we find significant positive intra-industry cumulative abnormal returns in the six-month and one-year event windows post announcement. Share price declines at credit downgrade announcements are reversed for transparent peer firms but continue their decline for opaque peer firms post announcement as information uncertainty is resolved and informed trading resumes. Taking the Fama-French (1993) and Carhart (1997) momentum asset pricing factors into account, more transparent firms have lower systematic risks and lower cost of capital. Transparent firms experience higher profitability in the year post-announcement.

The remaining sections of this paper are organized as follows. Section 2 reviews related literature and presents our hypotheses. Section 3 describes the data used for our analysis and our empirical design. Section 4 reports and discusses the spillover valuation effects at announcement and post-announcement. Robustness tests are presented in section 5. Section 6 concludes.

C. Background and Hypotheses

1. Earnings Transparency

Barth, Konchitchki, and Landsman (2013) argue that earnings transparency reflects the extent to which earnings disclosures are credible public signals about the fundamental value of firms. Lower uncertainty about intrinsic asset values diminishes the return investors require. The reduced cost of capital increases firm value. Investors will seek private information when the predictive content of earnings about firm value is poor, however, acquisition costs can be high when firms are complex entities. Moreover, gains to informed trading require sufficient market liquidity. Earnings transparency will remain important in mitigating the informational asymmetry between inside managers and outside investors.

The sum of explanatory powers (R^2) from a two-step estimation procedure of the returns-earnings relation capture the intertemporal industry and industry-neutral cross-sectional variations in earnings transparency. A significant negative relation between earnings transparency and subsequent excess and portfolio mean returns is documented. Taking Fama-French (1993) and Carhart (1997) momentum asset pricing factors into account, firms with more earnings transparency enjoy a lower cost of capital.

2. Return Synchronicity

Earnings as signals of economic value have limitations. Reporting standards and adoption can differ across firms as well as change over time. Earnings are historical rather than forward-looking. Innovation, expansion, acquisitions or divestitures can alter a firm's business and earnings power. The quality and clarity of disclosures can vary by firms as well. Last but not least, differences in performance based incentives influence when, what, and how managers exercise discretion.

Roll (1988) notes the extent to which stock returns move together will reflect macroeconomic, industry, as well as firm-specific factors. He finds however that firm size, industry, and the impact of unique industry or firm-specific news cannot explain the low degree of co-movement (R^2). Low return synchronicity, he concludes, can be due to "either the existence of private information or else occasional frenzy unrelated to concrete information (p.56)".

Morck, Yeung, and Yu (2000) find that emerging markets exhibit highly synchronous stock price movements. Moreover, return synchronicity is not related either to the size of the stock market or economy. Rather, the inadequate protection of property rights makes informed risk arbitrage unattractive. And as Delong, Shliefer, Summers, Waldmann (1989 and 1990) show, the reduction in informed trading can increase market-wide noise trading. Further, in countries that provide poor investor protection from corporate insiders, e.g. from earnings expropriation or risk-shifting behaviors, can render firm-specific information less useful. The reduction in firm-specific information in stock prices increases stock return synchronicity.

Durnev, Morck, Yeung, and Zarowin (2003) confirm that high firm-specific return variation as a fraction of total variation signals more informative stock prices. Regressions of current stock returns against future earnings are estimated to infer how much information stock prices contain about future earnings. Aggregated coefficients on future earnings and the marginal variation of current stock returns explained by future earnings capture the informativeness of stock prices. They find that firms and industries with lower market model R^2 exhibit higher association between current stock returns and future earnings. Markets are more information efficient.

Jones, Lee, and Yeager (2012a) argue that opacity exacerbates the variability in beliefs about an asset's fundamental value. Increased price uncertainty requires arbitrageurs to bear greater risk. The limits to informed arbitrage creates space for noise trading (Delong, Shleifer, Summers and Waldman, 1989 and 1990) that engenders positive feedback loops where the misconceptions of noise traders can prolong deviations of price from fundamental value. The inability of investors to discriminate across firms leads to return synchronicity (Roll 1998; Morck, Yeung, and Yu, 2000; Durnev, Morck, Yeung, and Zarowin, 2003). Investors use the information revealed about a specific firm to update their price expectations of similar but opaque firms. Using bank merger announcements, Jones, Lee, and Yeager (2012b) find that between 2000 and 2006, revaluations of banks not involved in the mergers were higher for more opaque banks. The most opaque non-merger banks with the highest revaluations prior to the financial crisis also experienced the largest price declines in the 2007-2008 financial crisis.

Further, the "separation of brains and capital" (Shleifer and Vishny, 1997) weakens the effectiveness of market discipline. Jones, Lee, and Yeager (2012b) find that valuation discounts associated with investments in opaque assets fell in the period 2000 to 2006. The fall in the required returns increased risk-taking in the years preceding the 2007 financial crisis. The resulting rise in return synchronicity, which peaked in 2007, created systemic risk.

3. Hypotheses

In this study, we conjecture that opacity impairs information efficiency. Investors will use public disclosures of credit downgrades to infer future changes in business and financial risks that confront similar firms in the same industry. But uncertainty about the causal risk factors that contributed to credit downgrades makes accurate assessments difficult and enables noise trading. Investors overreact to the potential adverse change in the creditworthiness of firms in the same industry as credit-downgraded firms. The contagion in equity share price declines of industry peer firms at credit downgrade announcements are reversed post announcement for transparent industry peer firms. For opaque industry peer firms, equity share price declines at credit downgrade announcements continue post announcement.

D. Empirical Design

1. Sample Selection

Our sample period starts in January 2000 and ends in December 2010. We excluded the years prior to the enactment of Reg FD in 2000. As noted earlier, a special exemption on selective disclosures of confidential information under Reg FD enhanced the informational advantage of credit ratings agencies. The enactment of the Dodd-Frank Wall Street and Consumer Protection Act of 2010 (Section 939B), however, removed the special exemption from Reg FD accorded statistical rating organizations and credit rating agencies for the purpose of determining or monitoring credit ratings.[7] Ending in 2010 also allowed us to examine the effects of credit rating changes in the year(s) following credit rating changes. A comprehensive list of Standard and Poor's (*S&P*) credit rating changes was compiled from Bloomberg Data Services. From this list, we focused on credit rating downgrades from investment grade (>=*BBB*-) to speculative grade (<=*BB*+) and conversely for upgrades. The list of event firms were then matched to the Center for Research in Securities Price (*CRSP*) database to obtain equity share prices around announcements of credit ratings changes.

To alleviate problems posed by thinly traded, illiquid securities and to ensure reliable estimates of abnormal returns, we required the equity shares of event firms to be traded at least 90% of the 282 days prior to the event date and 252 days following the event date. Moreover, to avoid potential biases with serial credit ratings changes, firms with more than one credit change event within a 366-day period were removed. Credit ratings changes by differing firms that occurred within the same industry over a period less than 15 days were also eliminated. Further, to avoid the potential for confounding effects of other corporate events in our abnormal returns calculations, we excluded any event firm which also had a merger announcement in the one month preceding or following the credit rating change. Event firms with share prices below $5 were also excluded. Lastly, financial firms with two-digit SIC codes in the interval 60-69 inclusive were discarded. The final sample contains 133 credit-downgrade events and 84 credit-

[7] Dimitrov, Palia, and Tang (2013) find that the increase in legal and regulatory penalties under Dodd-Frank made optimistic ratings costlier. As a result, credit ratings agencies issued lower ratings and gave more false warnings. Downgrades that were less informative because investors rationally discounted the private information of credit rating agency analysts.

upgrade events.[8]

As in prior studies, firms in the *Compustat* Annual database operating in the same three-digit Standard Industrial Classification code (*SIC*-3) as the event firm in the fiscal year immediately preceding the year of the ratings change announcement are considered peer firms.[9] Equity share prices for the 4,799 and 2,951 peer firms associated with credit downgrade and upgrade events respectively were obtained from the *CRSP* database. As with event firms, we required the equity shares of peer firms to be traded at least 90% of the 282 days prior to the event date and 252 days following the event date, and also that share prices of peer firms were greater than $5.

[Insert Table 1 here.]

The top panel of Table 1 reports, by year, the distribution of credit downgrade (upgrade) events, the mean number of peers, the mean *CAR*[-3,3] for the event firm, and the mean number of notches crossed in rating changes. As expected, macroeconomic conditions affect the frequency of credit downgrades. Credit downgrades occurred with greater frequency following the tech bubble collapse in 2000 as well as during the economic recession in 2001 and recovery in 2002 and 2003 that ensued. Credit upgrades are fewer in number and more likely in years of strong economic growth. The mean *CAR* for credit-downgraded event firms is negative regardless of the year and ranges from -23.16% in 2002 to -1.07% in 2007. The bottom panel of Table 1 shows considerable heterogeneity in the distribution of credit rating changes and peer firms across industries. Credit downgrades cluster in retail, machinery, and utility industries. Credit upgrades cluster in machinery and utilities industries. The mean number of peer firms per

[8]Our sample selection procedure is detailed in Appendix B.
[9]In unreported, random sample checks, we find the SIC codes given by *Compustat* better reflect the parent firm's SIC designation. However, our results are robust whether we use *Compustat* Annual or *CRSP* to identify peer firms.

industry are highest in the oil, machinery, cars, and utility industries and are lowest in transportation, construction, and clothing industries. On average, the number of peer firms in credit downgrades are roughly one-third less than in credit upgrades.

[Insert Table 2 here.]

Table 2 presents the pattern of credit upgrades and downgrades in our sample. The rows and columns of the matrix are the credit ratings of the event firms before and after the change, respectively. The numbers of ratings changes meeting the pre and post rating level are reported in the cells. For both upgrades and downgrades, the majority of credit change events involve a one-notch change across rating categories; e.g. from *BBB*- (*BB*+) to *BB*+ (*BBB*-). Note, however, that approximately 48.8% of the credit downgrades span more than one than one notch, and 31.5%, for credit upgrades. Altogether the pattern of credit upgrades and downgrades as well as the distribution across industries and over time show considerable variation in credit ratings changes.

2. Abnormal Equity Returns

To compute daily abnormal equity returns, a Fama-French (1993) three-factor plus Carhart (1997) momentum factor returns model is estimated over the period 282 days to 30 days prior to announcement date.[10]

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,RM}\left(R_{M,t} - R_{f,t}\right) + \beta_{i,SMB}R_{SMB,t} + \beta_{i,HML}R_{HML,t}$$
$$+\beta_{i,MOM}R_{MOM,t} + \varepsilon_{i,t} \qquad (1)$$

Daily abnormal equity returns summed over three-day, five-day, and seven-day event windows around announcement yield cumulative abnormal equity returns, *CAR*[-1,1], *CAR*[-3,1] and

[10]Our results are robust to various methods of calculating abnormal returns including a simple market adjustment, a one-factor market model, as well as a Fama-French (1993) three-factor returns model.

CAR[-3,3].[11] We use two proxies for the news content of credit rating changes. *Event Firm CAR*[-3,3] is the seven-day cumulative abnormal return of the credit ratings change firm at announcement. As in Holthausen and Leftwich (1986), *Notches* is a categorical variable that reflects the severity of the credit downgrade by the numerical drop in rating steps. For example, a ratings change from *BBB-* → *BB+* → *BB* generates a *Notches* value of -2. Summary descriptive statistics are reported in Table 3.

[Insert Table 3 here.]

CARs at announcement for credit downgraded and upgraded firms reported in the top panel of Table 3 are consistent with Holthausen and Leftwich (1986) and Dichev and Piotroski (2001). Credit-downgraded firms experience significantly negative abnormal equity returns. The mean *CAR*[-1,1], *CAR*[-3,1] and *CAR*[-3,3] are -5.26%, 6.89%, and -7.59% respectively; and, median *CARs*, are -2.13%, -2.82%, and -2.54% respectively. For upgrades, mean *CAR*[-1,1], *CAR*[-3,1] and *CAR*[-3,3] are positive, but are only significant in the three-day and five-day event windows and are much smaller in magnitude than for downgrades. Median *CARs* are not statistically significant.

Announcement *CARs* for peer firms exhibit a similar pattern. For credit ratings downgrades, mean (median) *CAR*[-1,1], *CAR*[-3,1], and *CAR*[-3,3] of -0.70% (-0.27%), -1.01% (-0.45%), and -1.09% (-0.44%), respectively are negative and statistically different from zero at better than the 1% level. For credit upgrades, mean and median *CARs* are considerably smaller in magnitude than for downgrades and largely indistinguishable from zero.

Credit ratings upgrades are largely anticipated. Regressions of peer firm *CARs* on event firm *CARs* and *Notches* with fixed effects for year and industry corroborate that spillover

[11]We also allowed our event window to range from as much as 10 days prior to 5 days after the event and found that our results remain qualitatively unchanged.

valuation effects are more significant for credit downgrades than credit upgrades. The information contagion is greater the more adverse is investor reaction to the credit downgrade. Peer firms benefit more when the competitive impairment of credit-downgraded firms is severe. From here on, we focus our analysis on credit ratings downgrades from investment to speculative grade.[12]

The remainder of Table 3 examines announcement returns around credit rating downgrades within investment grade and within speculative grade. Two key findings should be noted. First, our results support the findings of Jorion and Zhang (2010). Intra-industry revaluations at credit downgrades within investment grade reflect information contagion, and competitive effects for credit downgrades within speculative grade. Secondly, peer firms exhibit statistically significant, negative *CAR*s at credit downgrades within investment grade. But as the regression results show, average *CAR*s though negative are statistically insignificant when event firm *CARs* and *Notches* with fixed effects for year and industry are taken into account.

3. Peer Firm Characteristics

To examine how opacity impacts information efficiency, we construct proxies for the transparency of peer firms. As Roll (1998), Morck, Yeung, and Yu (2000), and Durnev, Morck, Yeung, and Zarowin (2003) argue, higher firm-specific return variation as a fraction of total variation implies a more informative equity share price. We use R^2 from a Fama-French (1993) three-factor plus Carhart (1997) momentum factor returns model estimated over the period 282 days to 30 days prior to the event date to capture the return synchronicity of peer firms. We compute *Return Synchronicity*, as the difference between the peer firm's R^2 and the

[12]In unreported analysis, we repeat all our subsequent tests on the sample of credit-upgraded firms and find no consistent announcement or post-announcement spillover valuation effects on peer firms.

median across all peers in the same event, to proxy for the informativeness of price. Peer firms are relatively more opaque (transparent) when their *Return Synchronicity* is positive (negative).

As a second measure of transparency, we also compute earnings transparency following Barth, Konchitchki, and Landsman (2013) as the summation of two R^2. The first R^2 is obtained from an earnings-returns relation regression shown in (2) estimated for each year (t = 2000, …, 2010) and for each Fama-French 17 industry.

$$RET_{i,j,t} = \alpha_0^I + \beta_1^I E_{i,j,t}/P_{i,j,t-1} + \beta_2^I \Delta E_{i,j,t}/P_{i,j,t-1} + \varepsilon_{i,j,t} \quad (2)$$

Subscripts i, j, and t denote firm, industry, and year, respectively. RET is the annual equity return of a firm measured beginning three months after the firm's fiscal year end, E_t/P_{t-1} is the earnings before extraordinary items and discontinued operations scaled by the beginning of year price, and ΔE is the change in earnings from year t-1 to t. Coefficients in (1), α_0^I, β_1^I, and β_2^I , are the same for firms within industry j in year t. R^2 in (2) captures the industry variation in returns in response to permanent and transitory components in earnings.

The magnitude of the residuals in the industry-year regressions (2) are then used each year to sort firms in each industry into quartiles to form portfolios p (p = 1, …, 4). Portfolios 1 and 4 have the largest negative and largest positive residuals respectively. A second earnings-return regression shown in (3) is estimated for each year and each portfolio.

$$RET_{i,p,t} = \alpha_0^{IN} + \beta_1^{IN} E_{i,p,t}/P_{i,p,t-1} + \beta_2^{IN} \Delta E_{i,p,t}/P_{i,p,t-1} + \varepsilon_{i,p,t} \quad (3)$$

R^2 in (3) captures the temporal variation in the industry neutral component of earnings transparency.

For each peer firm, *Earnings Transparency*, is the sum of their R^2 from (2) and (3). Higher values of *Earnings Transparency* are associated with greater firm transparency. As with return synchronicity, we subtract the median earnings transparency of all peers in the same event.

Positive (negative) values are associated with more transparent (opaque) peer firms.

Investor assessments of changes in creditworthiness from credit downgrades can differ between rated and unrated peer firms. Alissa, Bonsall, Koharki, and Penn (2013) use the log of total assets (*Ln*(TA)), sales and general administrative expenses scaled by revenue (*SGA*), asset tangibility (*PPE*), market-to-book (*MTB*), return on assets (*ROA*), solvency (*Altman-Z*), as well as research and development expenses scaled by total revenue (*R&D*), as surrogates for expected credit ratings.[13] Table 4A reports descriptive statistics for our sample of peer firms.

[Insert Table 4 here]

Median values for firm transparency, Return Synchronicity and Earnings Transparency, are zero by construction but show considerable heterogeneity. Return Synchronicity ranges from -0.3947 to 0.5670, and Earnings transparency, from -0.4064 to 0.7614. Approximately 27.6% of our sample of peer firms are rated by S&P.

Table 4B presents summary statistics by Fama-French 17 industries. The clothing industry is the most transparent industry with the lowest Return Synchronicity and highest Earnings Transparency. The most opaque industries are durables and steel with the highest Return Synchronicity, and oil, with the lowest Earnings Transparency. The percentage of peer firms with S&P rating is highest and lowest in the utilities and machinery industries.

Table 4C presents the Pearson (below diagonal) and Spearman rank correlations (above diagonal). Return Synchronicity and Earnings Transparency are negatively but not significantly rank correlated. The transparency measures capture distinct factors that contribute to information asymmetry.[14] Earnings Transparency reflects the quality of public disclosures by firms to

[13]Variable definitions are provided in appendix A.
[14]For Pearson correlation, *t*-statistic = $\rho/sqrt[(1-\rho^2)/(N-2)]$ is distributed Students t with $df = N-2$. For Spearman rank correlation, standard error $\sigma = 0.6325/(N-1)$.

investors. Return Synchronicity reflects the private information that investors have about the intrinsic values of firms.

Significant negative and positive correlations with Return Synchronicity and Earnings Transparency suggest that peer firms with high SGA tend to be more transparent. Peer firms that are larger, with higher asset tangibility and profitability, are more likely to be S&P rated. Conversely, peer firms with higher SGA, growth opportunities, solvency, and R&D expenditures are less likely to be S&P rated.

E. Empirical Results

1. Announcement Event CARs

Table 5 reports the results of cross-sectional OLS regressions of peer firm *CAR*[-3,3] with fixed effects for year and industry and robust standard errors clustered by industry. In these regressions, *Return Synchronicity and Earnings Transparency examine the effects of opacity*. The impact of *S&P* rating, *Event Firm CAR*[-3,3] and *Notches*, as well as the characteristics of the peer firms are taken into account.

[Insert Table 5 here]

Across model specifications, there is a significant negative intra-industry average *CAR*[-3,3] of about 1.24% at credit downgrade announcements. The share price decline corroborates an earlier finding in Table 3. Investors infer meaningful adverse changes in the creditworthiness of similar firms in the same industry.

The significant negative coefficient on *Return Synchronicity* and significant positive coefficient on *Earnings Transparency* show that share price declines are notably lower (higher) for transparent (opaque) firms. However, at best a small percentage of peer firms avoid a negative *CAR*[-3,3] at credit downgrade announcements. A one standard deviation change in

Return Synchronicity and *Earnings Transparency* implies about a -0.56% and 0.14% change in *CAR*[-3,3]. Given an average negative *CAR*[-3,3] of 1.24%, even peer firms whose *Return Synchronicity* are two standard deviations lower than median will experience a share price decline.

Credit downgrade announcements exacerbate investor beliefs about the creditworthiness and intrinsic value of similar firms in the same industry. Increased uncertainty and limits to arbitrage enables noise trading. On balance, investors overreact to potential adverse changes in creditworthiness of peer firms at credit downgrade announcements.

Further, at credit downgrade announcements, investors do not discriminate between *S&P* rated and unrated peer firms. Coefficients on *S&P Rated* and *Investment Rated* are positive but mainly insignificant. The positive significant *Event CAR*[-3,3] coefficient suggests information contagion is greater the more adverse is investor reaction to the credit downgrade. A one standard deviation change in *Event CAR*[-3,3] results in about a 1.66% change in *CAR*[-3,3]. Moreover, the negative significant *Notches* coefficient implies that peer firms benefit more when the competitive impairment of credit-downgraded firms is severe. The competitive effect is, however, small in magnitude. A one standard deviation change in *Notches* results in about a -0.28% change in *CAR*[-3,3].

Lastly, share price declines are significantly smaller for peer firms that are more profitable (*ROA*) and have lower *SGA*. A one standard deviation change in profitability and *SGA* results in about a 0.76% and -0.17% change in *CAR*[-3,3].

2. Post-Announcement Event CARs

To examine intra-industry post-announcement cumulative abnormal returns, we compute CARs over three-month, six-month, and one-year event window: *CAR*[4,68], *CAR*[4,130], and

CAR[4,256]. Table 6 reports the results of cross-sectional OLS regressions of peer firm post-announcement *CAR*s with fixed effects for year and industry and robust standard errors clustered by industry. In these regressions, *Return Synchronicity and Earnings Transparency examine the effects of opacity.* The impact of *S&P* rating, *Event Firm CAR*[-3,3] and *Notches*, as well as the characteristics of the peer firms are taken into account.

[Insert Table 6 here]

Significant negative *Event Firm CAR*[-3,3] at credit downgrade announcements are reversed post announcement. Across model specifications, three-month *CAR*[4,66] is a positive though insignificant 1.4% average. Six-month *CAR*[4,130] rises to a significant positive 4.7% average. Twelve-month *CAR*[4,130] evens out at a significant positive 4.9% average. Informed trading post announcement corrects investor overreaction at announcement.

The negative significant *Return Synchronicity* and positive significant *Earnings Transparency* coefficients indicate the reversal primarily benefit transparent peer firms. Share price declines continue for opaque peer firms with higher than median *Return Synchronicity* and lower than median *Earnings Transparency*. A one standard deviation change in *Return Synchronicity* and *Earnings Transparency* implies about a -2.76% and 2.72% change in *CAR*[4,130] and about a -5.37% and 4.68% change in *CAR*[4,256]. Given an average negative *CAR*[4,256] of 4.9%, opaque peer firms whose *Return Synchronicity* or *Earnings Transparency* are one standard deviation higher or lower than median will experience a share price decline post-announcement.

The information contagion associated with credit downgrades are fully reflected in *Event Firm CAR*[-3,3]. The benefits to peer firms from the competitive impairment of credit-downgraded firms are transient and reverse in the six months following announcement. From the correlation table in Table 4C, coefficient signs on significant firm characteristics suggest that post-announcement returns are higher for unrated and more creditworthy peer firms. The former are smaller in size (*Ln(TA)*), high *SGA*, high solvency (*Altman-Z*), and invest in *R&D*. The latter are lower growth (*MTB*) and higher profitability (ROA).

3. Uncertainty Resolution

Post-announcement abnormal equity returns are computed on the assumption that systematic risk (beta) exposures estimated in the pre-announcement period remain unchanged following credit downgrades. But heightened uncertainty about the creditworthiness and intrinsic value of similar firms in the same industry as credit-downgraded firms may raise investors' perceptions of systematic risks. Positive post-announcement *CAR*s may simply reflect a latent change in systematic risk (beta) exposures.

We conjecture, however, that information uncertainties are gradually resolved post-announcement. The release of quarterly earnings reduces the informational asymmetry between firms and outside investors. When *Earnings Transparency* is high (low), disclosures are informative about the creditworthiness and intrinsic values of peer firms. Further, credit downgrade announcements that intensity investor uncertainties also enhance the incentives to acquire private information. Share price changes post announcement are more likely to signal informed trading.

We examine our conjecture in an asset pricing framework. At each event, peer firms are assigned into quartiles sorted by their values of *Return Synchronicity*, *Earnings Transparency*, and summed ranks on *Return Synchronicity* and *Earnings Transparency*. *Return Synchronicity* and *Earnings Transparency* are both estimated in the pre-announcement period. By each measure of transparency, peer firms sorted into portfolios 1 to 4 represent the least transparent and most transparent respectively across all events.

Using a Fama-French (1993) three factor and Carhart (1997) momentum factor returns model, we estimate seemingly unrelated regressions (Zellner, 1962).

$$R_{it} - R_{ft} = \alpha_p + \beta_{RMRF,p}(R_{Mt} - R_{ft}) + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \beta_{Rated,p}S\&P\ Rated_i + \beta_{IG,p}Investment\ \ Grade_i + \beta_Z Z_i + \varepsilon_{it} \quad (4)$$

i denotes peer firms in portfolio p. Beta coefficients for peer firms differ only across portfolios. We include proxies for rating – $S\&P\ Rated_i$ and $Investment\ \ Grade_i$, as well as Z_i, a vector of event and peer firm characteristics – *Event CAR*[-3,3], *Notches*, *Ln(TA)*, *SGA*, *PPE*, *MTB*, *ROA*, *Altman-Z*, and *R&D*. Regressions control for year and industry fixed effects and compute robust standard errors clustered by industry. In (4), $\beta_{RMRF,p}$, $\beta_{SMB,p}$, $\beta_{HML,p}$, and $\beta_{UMD,p}$ characterize the systematic risk exposures on the least to most transparent quartile portfolios across events over the one-year post-announcement event window [4,256]. α_p denotes the excess risk-adjusted returns on the least to most transparent quartile portfolios of peer firms across events over the one-year post-announcement event window [4,256]. Results are presented in Table 7.

[Insert Table 7 here]

The left-hand panel of Table 7 utilize portfolios formed by *Return Synchronicity*. The 2 basis point abnormal daily return (alpha) on portfolio (1) with the least transparent peer firms is not significantly different from zero. As expected, daily abnormal returns increase monotonically in magnitude and statistical significance with transparency. The 8 basis point abnormal daily return on portfolio (4) is significant. Moreover, the positive difference in abnormal daily return between portfolio (4) and (1) of 6 basis points is significant at better than the 1% level (*F*-statistic = 17.9).

Further, note that systematic risks are significantly higher for opaque peer firms. β_{RMRF} is 1.09 for portfolio (1) and decreases monotonically to 0.51 for portfolio (4). Similarly, β_{SMB} is 0.66 for portfolio (1) and declines to 0.42 for portfolio (4). A negative significant β_{UMD} for portfolio (1) suggests that returns on opaque peer firms exhibit reversals rather than momentum.

Lastly, positive significant β_{Rated} and negative significant $\beta_{Investment\ Grade}$ coefficients suggest that *S&P* speculative grade peer firms are more risky than *S&P* investment grade peer firms. *S&P* speculative grade peer firms tend to be opaque. *S&P* investment grade peer firms tend to be transparent.

The results in the middle panel of Table 7 based on portfolios formed by *Earnings Transparency* are qualitatively similar. The 3 basis point abnormal daily return (alpha) on portfolio (1) with the least transparent peer firms is not significantly different from zero. As in Barth, Konchitchki, and Landsman (2013), daily abnormal returns increase (non-monotonically) in magnitude and statistical significance with transparency. The 9 basis point abnormal daily return on portfolio (4) is significant. Moreover, the positive difference in abnormal daily return between portfolio (4) and (1) of 6 basis points is significant at better than the 1% level (*F*-statistic = 15.4).

Again, note that systematic risks are higher for opaque peer firms. β_{RMRF} is 0.90 for portfolio (1) and decreases monotonically to 0.86 for portfolio (4). Similarly, β_{SMB} is 0.66 for portfolio (1) and declines to 0.60 for portfolio (4). A negative significant β_{UMD} for portfolio (1) corroborates that returns on opaque peer firms exhibit reversals rather than momentum. Lastly, positive significant β_{Rated} and negative significant $\beta_{Investment\ Grade}$ coefficients substantiate that *S&P* speculative grade peer firms are more risky than *S&P* investment grade peer firms.

Lastly, the negative significant *Event CAR*[-3,3] coefficient in the bottom left-hand and middle panels of Table 7 shows a post-announcement reversal of the information contagion associated with investors' reaction to credit downgrades consistent with a resolution of information uncertainty. From the correlation table in Table 4C, coefficient signs on significant firm characteristics indicate that post-announcement returns are higher for unrated and more creditworthy peer firms. The former are smaller in size (*Ln(TA)*), high *SGA*, high solvency (*Altman-Z*), and invest in *R&D*. The latter are lower growth (*MTB*) and higher profitability (*ROA*).

The results in the right-hand panel of Table 7 confirm the left-hand and middle panels of Table 7. Overall, the findings support the thesis that post-announcement abnormal returns reflect a resolution of information uncertainty and informed trading. At credit downgrade announcements, investors overreact to the potential adverse changes in the creditworthiness and intrinsic values of similar firms in the same industry. The overreactions are corrected post-announcement for transparent peer firms.

4. Changes in Profitability

Credit rating changes signal revisions in the beliefs of rating agencies about the latent intrinsic values of rated firms. Ederington and Goh (1998) find that analysts forecast declines (growth) in quarterly earnings per share prior and subsequent to credit rating downgrades (upgrades). Further, there are significant decreases in actual earnings per share prior and subsequent to credit downgrades, but insignificant increases, for credit upgrades. Similarly, Dichev and Piotroski (2001) find strongly (weakly) significant decreases (increases) in annual earnings following credit downgrades (upgrades).

In this section we examine three proxies for post-announcement changes in the profitability of firms in the same industry as credit-downgraded firms – $\Delta ROA[-1,1]$, $\Delta Profit$[-

1,1], and Δ*EPS*[-1,1]. Each proxy is constructed as the difference in profitability between the fiscal year following and fiscal year prior to the fiscal year of the ratings change. For example, for a ratings change that occurred in fiscal year 2003, the difference is the profitability in fiscal year end 2004 and fiscal year end 2002. Variable definitions are provided in Appendix A.

Table 8 reports the results of cross-sectional OLS regressions of peer firm post-announcement profitability with fixed effects for year and industry and robust standard errors clustered by industry. In these regressions, *Return Synchronicity and Earnings Transparency examine the effects of opacity.* The impact of *S&P* rating, Event Firm *CAR*[-3,3] and *Notches*, as well as the characteristics of the peer firms are taken into account.

[Insert Table 8 here]

Across model specifications, Δ*ROA*[-1,1], Δ*Profit*[-1,1], and Δ*EPS*[-1,1], average 1.2%, 7.2%, and 0.55 respectively. Δ*Profit*[-1,1] and Δ*EPS*[-1,1] are significant at better than the 1% level; Δ*ROA*[-1,1] is marginally significant at the 15% level. The changes in profitability are consistent with uncertainty resolution and informed trading post announcement which corrects investor overreaction at announcement.

The negative significant *Return Synchronicity* and positive significant *Earnings Transparency* coefficients indicate improved profitability post-announcement are primarily focused on transparent peer firms. Profitability declines continue for opaque peer firms with higher than median *Return Synchronicity* and lower than median *Earnings Transparency*. A one standard deviation change in *Return Synchronicity* and *Earnings Transparency* imply about a -0.86%, -1.56%, and -7.73% and about a 0.40%, 0.85%, and 8.07% change in Δ*ROA*[-1,1], Δ*Profit*[-1,1], and Δ*EPS*[-1,1], respectively.

Lastly, negative and significant *Event CAR*[-3,3] and *Notches* coefficients show that the impaired competitiveness of credit-downgraded firms improve the profitability of peer firms. Post-announcement profitability is higher for high growth (*MTB*), and lower for more solvent (Altman-Z), peer firms.

F. Conclusion

This paper examines the spillover effects of long-term issuer credit-downgrades on similar firms in the same industry. We show the opacity of firms hinders information efficiency. Investors infer adverse changes in the creditworthiness and intrinsic values of peer firms at credit downgrade announcements. Increased uncertainty among investors about economic fundamentals, however, limits arbitrage and enables noise trading. The inflated share price declines at credit downgrade announcements are reversed post announcement as information uncertainties about peer firms are resolved. Transparent firms benefit the most from the reduction in information asymmetry and increased informed trading post announcement.

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Table 1: Distribution of Credit Events

Sample events are long-term credit rating downgrades (upgrades) from investment (speculative) to speculative (investment) grade over the period January 1, 2000 through December 31, 2010. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the credit rating change firm in the announcement year. Top and bottom panels report the distribution of events, average number of peer firms, average 7-day cumulative abnormal return on credit rating change firms, and average number of notches involved in credit rating changes by year and industry, respectively. Daily abnormal returns for credit change firms are computed using the Fama-French (1993) three-factor plus Carhart (1997) momentum factor returns model estimated over the period 282 to 30 days prior to announcement.

Table 1: Distribution of Credit Events (Cont.)

Year	Credit Rating Downgrades Investment to Speculative Grade: No. of Events	Average Number of Peers	Average Event Firm *CAR*[-3,3]	Average No. of Notches	Credit Rating Upgrades Speculative to Investment Grade: No. of Events	Average Number of Peers	Average Event Firm *CAR*[-3,3]	Average No. of Notches
2000	9	21.3	-0.0746	-1.78	7	35.1	0.0278	1.57
2001	23	56.8	-0.1040	-2.43	4	49.5	0.0194	1.75
2002	16	25.9	-0.2316	-1.88	4	18.8	0.0136	1.00
2003	22	21.6	-0.0503	-1.50	4	35.0	0.0270	1.50
2004	9	77.0	-0.0215	-1.56	8	25.4	0.0276	1.13
2005	12	15.9	-0.0470	-1.25	13	77.8	0.0016	1.31
2006	11	54.8	-0.0269	-1.64	6	73.5	-0.0048	1.17
2007	11	19.1	-0.0107	-1.82	13	43.2	-0.0085	1.31
2008	13	54.2	-0.0317	-1.31	9	23.0	0.0222	1.11
2009	5	4.4	-0.1202	-1.40	7	69.9	0.0004	1.29
2010	2	14.0	-0.0183	-1.50	9	12.8	0.0005	1.00
Total	***133***	***36.4***	***-0.0759***	***-1.72***	***84***	***43.9***	***0.0089***	***1.26***

Fama-French Industries	No. of Events	Average Number of Peers	Average Event Firm *CAR*[-3,3]	Average No. of Notches	No. of Events	Average Number of Peers	Average Event Firm *CAR*[-3,3]	Average No. of Notches
FOOD	-	-	-	-	-	-	-	-
MINING	2	10.0	-0.0340	-2.00	2	12.5	0.0656	2.00
OIL	4	72.0	-0.2640	-1.25	4	85.3	0.0151	1.00
CLTHS	4	6.5	-0.0112	-1.50	2	17.5	-0.0142	1.00
DURBL	7	14.3	-0.0289	-1.43	2	14.5	0.0234	1.00
CHEM	6	10.8	-0.0405	-1.00	2	12.0	0.0491	1.00
CNSUM	-	-	-	-	3	8.7	-0.0377	1.00
CNSTR	7	4.1	-0.1225	-1.71	4	4.3	0.0342	1.25
STEEL	5	16.6	-0.1536	-2.00	1	23.0	0.0779	1.00
FABPR	-	-	-	-	-	-	-	-
MACHN	13	59.2	-0.0350	-1.54	16	74.3	0.0062	1.19
CARS	7	33.4	-0.0309	-1.71	4	32.3	0.0148	1.25
TRANS	5	8.4	-0.1059	-1.20	1	13.0	-0.0534	1.00
UTILS	13	32.3	-0.2134	-3.38	10	29.2	-0.0086	1.50
RTAIL	19	15.2	-0.0248	-1.47	7	18.9	0.0141	1.14
OTHER	41	60.4	-0.0588	-1.61	26	54.4	0.0084	1.35
TOTAL	***133***	***36.4***	***-0.0759***	***-1.72***	***84***	***43.9***	***0.0089***	***1.26***

Table 2: Credit Rating Change Matrix

This table reports the distribution of *S&P* long-term credit rating downgrades (upgrades) from investment (speculative) to speculative (investment) grade over the period January 1, 2000 through December 31, 2010. The rows and columns are the long-term credit ratings before and after the rating change events.

Panel A: Credit Rating Downgrades

	New Rating							
Old Rating	***BB+***	***BB***	***BB-***	***B+***	***B***	***B-***	***CC***	***C***
A+	0	0	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0
A-	0	0	0	0	0	0	0	0
BBB+	4	0	0	0	0	0	0	0
BBB	14	5	3	1	0	0	0	0
BBB-	76	25	3	0	0	0	2	0

Panel B: Credit Rating Upgrades

	New Rating							
Old Rating	***AAA***	***AA-***	***A+***	***A***	***A-***	***BBB+***	***BBB***	***BBB-***
BB+	0	0	0	0	0	0	11	63
BB	0	0	0	0	0	0	0	9
BB-	0	0	0	0	0	0	0	1
B+	0	0	0	0	0	0	0	0
B	0	0	0	0	0	0	0	0
CCC	0	0	0	0	0	0	0	0

Table 3: Announcement Returns

Table reports descriptive statistics on cumulative abnormal equity returns around credit downgrades and upgrades over the sample period January 1, 2000 through December 31, 2010. Daily abnormal returns for event (credit ratings change) firms and associated peers are computed using the Fama-French (1993) three-factor plus Carhart (1997) momentum factor returns model estimated over the period 282 to 30 days prior to announcement. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the event (credit rating change) firm in the announcement year. Cross-sectional OLS regressions of cumulative abnormal returns (*CARs*) of peers control for fixed effects by year and industry using Fama-French (1997) 17-industry classification and robust standard errors clustered by industries. *Event Firm CAR*[-3,3] and *Notches* are demeaned by cross-sectional average. *t*-statistics are presented in parentheses. *p*-values on joint coefficient restriction tests are reported in brackets. *, **, ***, denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Announcement Returns (Cont.)

		Credit Rating Downgrades Investment to Speculative Grade				*Credit Rating Upgrades* Speculative to Investment Grade		
	N	***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***	***N***	***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***
Event Firms								
Mean	133	-0.0526 ***	-0.0689 ***	-0.0759 ***	84	0.0066 **	0.0088 **	0.0089
Medan	133	-0.0213 ***	-0.0282 ***	-0.0254 ***	84	0.0052	0.0018	0.0012
Standard Deviation	133	0.1264	0.1598	0.1774	84	0.0281	0.0352	0.0442
25th Percentile	133	-0.0664	-0.0957	-0.1010	84	-0.0143	-0.0142	-0.0246
75th Percentile	133	0.0092	0.0087	0.0117	84	0.0302	0.0385	0.0464
Peer Firms								
Mean	4,799	-0.0070 ***	-0.0101 ***	-0.0109 ***	3,648	0.0002	-0.0001	0.0031 *
Medan	4,799	-0.0027 ***	-0.0045 ***	-0.0044 ***	3,648	-0.0016	-0.0017 **	0.0000
Standard Deviation	4,799	0.0604	0.0788	0.0895	3,648	0.0574	0.0769	0.0920
25th Percentile	4,799	-0.0329	-0.0421	-0.0489	3,648	-0.0271	-0.0352	-0.0390
75th Percentile	4,799	0.0242	0.0305	0.0375	3,648	0.0224	0.0289	0.0388
***Peer Firm CAR* Regressions**		***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***		***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***
Constant		-0.0080 ***	-0.0144 ***	-0.0116 ***		-0.0054	-0.0102 *	-0.0263
		(-4.839)	(-4.323)	(-3.302)		(-1.506)	(-1.779)	(-1.444)
Event Firm $\boldsymbol{CAR[-3,3]}$		0.0378 ***	0.0580 ***	0.0542 ***		0.0664 **	0.0797 **	0.1041 *
		(12.151)	(8.624)	(10.629)		(2.122)	(2.025)	(1.737)
Demeaned Notches		-0.0022 ***	-0.0016 ***	-0.0029 ***		-0.0020	-0.0006	-0.0068
		(-5.272)	(-3.161)	(-6.806)		(-0.462)	(-0.136)	(-1.604)
Adjusted $\boldsymbol{R^2}$		0.051	0.070	0.045		0.036	0.026	0.026
Constant		-0.0074 ***	-0.0133 ***	-0.0091 **		-0.0039 **	-0.0028	0.0062
		(-5.235)	(-3.885)	(-2.529)		(-2.285)	(-0.775)	(1.315)
Event Firm $\boldsymbol{CAR[-3,3]}$		0.0379 ***	0.0580 ***	0.0543 ***		0.0649 **	0.0813 **	0.1040 **
		(7.929)	(7.346)	(8.962)		(1.988)	(2.028)	(1.743)
Demeaned Notches		-0.0010	0.0014	0.0034		-0.0026	0.0037	-0.0047
		(-0.594)	(0.443)	(1.050)		(-0.548)	(0.727)	(-0.872)
Rival		-0.0011	-0.0023	-0.0051		0.0027	0.0045 *	0.0044
		(-0.358)	(-1.013)	(-1.383)		(1.145)	(1.700)	(1.313)
Rival* × *Demeaned		-0.0015	-0.0035	-0.0073 **		0.0014	-0.0074	-0.0034
		(-0.724)	(-1.061)	(-2.350)		(0.264)	(-1.064)	(-0.456)
Adjusted $\boldsymbol{R^2}$		0.051	0.070	0.047		0.037	0.026	0.027

Table 3: Announcement Returns (Cont.)

	Credit Rating Downgrades Within Investment Grade				Credit Rating Downgrades Within Speculative Grade			
	N	***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***	***N***	***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***
Event Firms								
Mean	992	-0.006 ***	-0.0087 ***	-0.0099***	1,094	-0.013 ***	-0.0136 ***	-0.0155 ***
Medan	992	-0.002 **	-0.0053 ***	-0.0058 ***	1,094	-0.006 ***	-0.0055 ***	-0.0063 ***
Standard Deviation	992	0.043	0.0532	0.0602	1,094	0.067	0.0813	0.0930
25th Percentile	992	-0.025	-0.0327	-0.0380	1,094	-0.038	-0.0502	-0.0604
75th Percentile	992	0.017	0.0237	0.0257	1,094	0.023	0.0320	0.0373
Peer Firms								
Mean	39,348	-0.0018 ***	-0.0010 ***	-0.0009 **	42,428	-0.0002	0.0005	0.0009 *
Medan	39,348	-0.0018 ***	-0.0013 ***	-0.0011 ***	42,428	-0.0011 ***	-0.0005 *	-0.0005
Standard Deviation	39,348	0.0479	0.0620	0.0727	42,428	0.0498	0.0655	0.0775
25th Percentile	39,348	-0.0280	-0.0350	-0.0416	42,428	-0.0287	-0.0370	-0.0444
75th Percentile	39,348	0.0235	0.0321	0.0388	42,428	0.0269	0.0366	0.0441
***Peer Firm CAR* Regressions**		***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***		***CAR[-1,1]***	***CAR[-3,1]***	***CAR[-3,3]***
Constant		-0.0007	-0.0039	-0.0056		0.0014	0.0015	-0.0004
		(-0.344)	(-1.066)	(-1.372)		(0.397)	(0.327)	(-0.056)
Event Firm $\boldsymbol{CAR[-3,3]}$		0.0365 ***	0.0559 ***	0.0799 ***		0.0377 ***	0.0563 ***	0.0896 ***
		(2.950)	(3.975)	(4.468)		(4.004)	(3.843)	(3.989)
Notches		-0.0002	-0.0006	-0.0002		0.0003	0.0004	-0.0001
		(-0.303)	(-0.759)	(-0.220)		(0.339)	(0.348)	(-0.074)
Adjusted R^2		0.006	0.007	0.008		0.007	0.010	0.016
Constant		-0.0035 **	-0.0017	-0.0017		-0.0023 ***	-0.0013	-0.0015
		(-2.054)	(-0.810)	(-0.733)		(-4.184)	(-1.600)	(-1.608)
Event Firm $\boldsymbol{CAR[-3,3]}$		0.0368 ***	0.0563 ***	0.0801 ***		0.0374 ***	0.0560 ***	0.0891 ***
		(2.925)	(3.924)	(4.432)		(3.993)	(3.832)	(3.989)
Demeaned Notches		-0.0009	-0.0015 **	-0.0009		0.0012	0.0013	0.0014
		(-1.164)	(-2.057)	(-1.327)		(1.010)	(0.819)	(0.953)
Rival		-0.0006	-0.0014	-0.0004		0.0007	0.0016 ***	0.0019 ***
		(-0.760)	(-1.049)	(-0.223)		(0.759)	(2.734)	(2.598)
Rival × ***Demeaned***		0.0014 *	0.0020 ***	0.0013		-0.0015 *	-0.0016	-0.0026 ***
		(1.720)	(3.260)	(1.505)		(-1.876)	(-1.468)	(-3.507)
Adjusted R^2		0.007	0.007	0.008		0.007	0.010	0.016

Table 4: Transparency and Peer Firm Characteristics

Table reports descriptive statistics on return synchronicity and earnings transparency measures as well as financial characteristics of peer firms in our sample. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the event (credit rating change) firm in the announcement year. Variable definitions are provided in Appendix A. Panels A and B present summary statistics for the overall sample and by Fama-French (1997) industry, respectively. Correlations are shown in Panel C. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Pooled Sample

NOBS = 4,799	**Mean**	**Median**	**Standard Deviation**	**5th Percentile**	**25th Percentile**	**75th Percentile**	**95th Percentile**
Return Synchronicity	0.0138	0.0000	0.1254	-0.1682	-0.0700	0.0896	0.2521
Earnings Transparency	0.0064	0.0000	0.0847	-0.0767	-0.0098	0.0061	0.1454
S&P Rated	0.2761	0.0000	0.4471	0.0000	0.0000	1.0000	1.0000
Ln(TA)	6.0776	5.8749	2.0230	2.8996	4.5154	7.5391	9.9731
SGA	0.3692	0.2809	0.3311	0.0000	0.1094	0.5480	1.2040
PPE	0.2587	0.1550	0.2444	0.0215	0.0621	0.4090	0.8074
MTB	1.6903	1.3627	0.9414	0.6390	1.0318	2.0906	4.1176
ROA	0.0066	0.0505	0.1309	-0.2775	-0.0421	0.0975	0.1508
Altman-Z	3.3560	2.6352	4.0997	-4.1977	1.1862	4.8555	13.6695
R&D	0.5803	1.0000	0.4936	0.0000	0.0000	1.0000	1.0000

Table 4: Transparency and Peer Firm Characteristics (Cont.)

Panel B: By Industry

	R - Sync		E - Trans		Rated		Ln(TA)		SGA		PPE		MTB		ROA		Altman-Z		RD-Ind.	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
MINING	-0.012	0.156	-0.003	0.017	0.47	0.51	7.45	2.04	0.12	0.28	0.56	0.19	1.50	0.91	0.04	0.13	4.98	4.41	0.26	0.45
OIL	0.025	0.112	-0.020	0.150	0.44	0.50	6.59	2.06	0.19	0.27	0.72	0.15	1.54	0.79	0.06	0.10	2.75	3.09	0.07	0.25
CLTHS	-0.021	0.176	0.060	0.235	0.19	0.40	6.07	1.28	0.35	0.16	0.17	0.12	1.81	0.90	0.08	0.11	5.66	4.25	0.08	0.27
DURBL	0.031	0.123	0.003	0.022	0.22	0.42	5.55	1.54	0.27	0.19	0.27	0.16	1.39	0.73	0.03	0.12	3.88	3.21	0.57	0.50
CHEM	0.000	0.176	0.059	0.177	0.55	0.50	6.81	2.01	0.14	0.08	0.36	0.17	1.49	0.63	0.04	0.09	2.87	2.72	0.75	0.44
CNSTR	0.020	0.120	0.002	0.029	0.36	0.49	6.51	1.50	0.19	0.22	0.34	0.22	1.15	0.46	0.04	0.10	2.96	1.64	0.36	0.49
STEEL	0.031	0.139	0.040	0.129	0.58	0.50	6.88	1.63	0.11	0.08	0.41	0.13	1.20	0.59	0.04	0.07	2.60	1.76	0.54	0.50
MACHN	0.015	0.142	0.015	0.098	0.15	0.36	5.41	1.83	0.45	0.31	0.15	0.12	1.78	0.97	-0.03	0.15	4.36	4.66	0.93	0.26
CARS	0.003	0.134	-0.001	0.103	0.45	0.50	7.03	1.91	0.13	0.08	0.28	0.13	1.32	0.72	0.06	0.08	3.58	2.99	0.79	0.41
TRANS	0.008	0.123	0.011	0.038	0.46	0.50	7.08	1.67	0.07	0.06	0.65	0.19	1.31	0.70	0.07	0.07	2.65	2.89	0.05	0.22
UTILS	-0.014	0.113	0.004	0.115	0.86	0.35	8.56	1.35	0.00	0.02	0.61	0.14	1.12	0.22	0.06	0.03	1.26	0.56	0.00	0.00
RTAIL	0.001	0.119	0.003	0.085	0.37	0.48	6.90	1.66	0.24	0.11	0.40	0.19	1.67	0.92	0.08	0.07	4.75	2.58	0.03	0.16
OTHER	0.019	0.119	0.006	0.046	0.15	0.36	5.56	1.83	0.49	0.33	0.14	0.17	1.86	1.01	-0.02	0.14	3.29	4.55	0.69	0.46

Panel C: Pearson (Spearman) Correlations Below (Above) Diagonal

	P - Sync	E - Trans	S&P Rated	*Ln* (TA)	SGA	PPE	MTB	ROA	Altman-Z	RD-Ind.
P - Sync	**1.000**	-0.016	0.220 ***	0.463 ***	-0.034 **	0.027 *	0.207 ***	0.207 ***	0.201 ***	0.081 ***
E - Trans	-0.029 **	**1.000**	-0.004	-0.001	0.024 *	-0.021	-0.002	0.016	0.021	0.015
S&P Rated	0.211 ***	-0.022	**1.000**	0.670 ***	-0.475 ***	0.433 ***	-0.216 ***	0.261 ***	-0.195 ***	-0.295 ***
Ln (TA)	0.408 ***	-0.022	0.689 ***	**1.000**	-0.535 ***	0.444 ***	-0.221 ***	0.446 ***	0.007	-0.276 ***
SGA	-0.026 *	0.026 *	-0.419 ***	-0.526 ***	**1.000**	-0.585 ***	0.298 ***	-0.462 ***	0.008	0.515 ***
PPE	-0.014	-0.041 ***	0.436 ***	0.438 ***	-0.505 ***	**1.000**	-0.277 ***	0.241 ***	-0.178 ***	-0.503 ***
MTB	0.171 ***	0.016	-0.222 ***	-0.241 ***	0.270 ***	-0.259 ***	**1.000**	0.128 ***	0.320 ***	0.245 ***
ROA	0.162 ***	-0.003	0.289 ***	0.488 ***	-0.641 ***	0.266 ***	-0.015	**1.000**	0.464 ***	-0.251 ***
Altman-Z	0.177 ***	0.023	-0.157 ***	0.005	-0.115 ***	-0.163 ***	0.353 ***	0.420 ***	**1.000**	0.102 ***
RD-Ind.	0.105 ***	0.036 **	-0.295 ***	-0.274 ***	0.470 ***	-0.551 ***	0.239 ***	-0.277 ***	0.085 ***	**1.000**

Table 5: Announcement Return Regressions

Table reports results of cross-sectional OLS regressions of cumulative abnormal returns (*CARs*) of peer firms with fixed effects for year and robust standard errors clustered by industries. Daily abnormal equity returns in the event windows are computed using a Fama-French (1993) three-factor plus Carhart (1997) momentum factor returns model estimated over the period 282 to 30 days prior to announcement. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the event firm in the announcement year. *Event Firm CAR*[-3,3], *Notches*, *Ln(TA)*, *SGA*, *PPE*, *MTB*, *ROA*, and *Altman-Z* are demeaned by the cross-sectional average. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Economic significance represents the impact on *CARs* associated with one standard deviation change.

	Dependent Variable: Peer Firm $CAR[-3,3]$			
Constant	-0.0129 ***	-0.0123 ***	-0.0130 ***	-0.0124 ***
	(-9.625)	(-8.811)	(-9.516)	(-8.665)
Return Synchronicity		-0.0443 ***		-0.0439 ***
		(-2.789)		(-2.741)
Earnings Transparency			0.0180 *	0.0162
			(1.763)	(1.538)
S&P Rated (Yes=1)	0.0025	0.0026	0.0025	0.0026
	(0.661)	(0.720)	(0.669)	(0.727)
Investment Rated	0.0047	0.0043	0.0048 *	0.0045
	(1.586)	(1.381)	(1.653)	(1.423)
***Event CAR*[-3,3]**	0.0634 ***	0.0635 ***	0.0632 ***	0.0633 ***
	(6.600)	(6.636)	(6.429)	(6.475)
Notches	-0.0022 ***	-0.0024 ***	-0.0023 ***	-0.0024 ***
	(-3.442)	(-3.763)	(-3.574)	(-3.891)
Ln(TA)	-0.0022 **	-0.0001	-0.0022 **	-0.0002
	(-2.228)	(-0.113)	(-2.229)	(-0.134)
SGA	-0.0076 ***	-0.0060 **	-0.0077 ***	-0.0062 **
	(-2.622)	(-2.381)	(-2.721)	(-2.482)
PPE	0.0005	0.0017	0.0002	0.0015
	(0.063)	(0.229)	(0.033)	(0.201)
MTB	-0.0009	0.0002	-0.0009	0.0002
	(-0.953)	(0.219)	(-0.961)	(0.194)
ROA	0.0681 ***	0.0660 ***	0.0677 ***	0.0657 ***
	(7.181)	(6.700)	(7.316)	(6.820)
Altman-Z	0.0007	0.0008	0.0007	0.0008
	(1.225)	(1.633)	(1.226)	(1.630)
R&D	-0.0005	-0.0001	-0.0006	-0.0001
	(-0.330)	(-0.042)	(-0.347)	(-0.060)
Adjusted R^2	0.052	0.055	0.053	0.055

Table 6: Post-Announcement Return Regressions

Table reports results of cross-sectional OLS regressions of cumulative abnormal returns (*CAR*s) of peer firms with fixed effects for year and industry using Fama and French 17 industry classifications and robust standard errors clustered by industries. Daily abnormal equity returns in the event windows are computed using a Fama-French (1993) three-factor plus Carhart (1997) momentum factor returns model estimated over the period 282 to 30 days prior to announcement. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the event firm in the announcement year. *Event Firm CAR*[-3,3], *Notches*, *Ln(TA)*, *SGA*, *PPE*, *MTB*, *ROA*, and *Altman-Z* are demeaned by their respective cross-sectional averages. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 6: Post-Announcement Return Regressions (Cont.)

	S&P Rated			Price Synchronicity			Earnings - Transparency			Full Model		
	CAR[4,68]	CAR[4,130]	CAR[4,256]	CAR[4,68]	CAR[4,130]	CAR[4,256]	CAR[4,68]	CAR[4,130]	CAR[4,256]	CAR[4,68]	CAR[4,130]	CAR[4,256]
β_1: P - Synchronicity				-0.0829 *	-0.2250 ***	-0.4363 ***				-0.0809 *	-0.2161 ***	-0.4210 ***
				(-1.867)	(-4.244)	(-5.347)				(-1.768)	(-4.243)	(-4.859)
β_2: E - Transparency							0.0744	0.3257 ***	0.5610 ***	0.0712	0.3172 ***	0.5444 ***
							(1.216)	(5.221)	(8.337)	(1.160)	(5.070)	(7.944)
S&P Rated (1 if yes)	0.0089	0.0161	0.0255	0.0091	0.0166	0.0265	0.0089	0.0161	0.0255	0.0091	0.0166	0.0265
	(0.789)	(0.876)	(1.285)	(0.807)	(0.950)	(1.462)	(0.779)	(0.899)	(1.350)	(0.796)	(0.969)	(1.522)
Investment Rated	-0.0079	0.0121	0.0027	-0.0087	0.0100	-0.0014	-0.0073	0.0149	0.0075	-0.0081	0.0128	0.0033
	(-0.483)	(0.737)	(0.092)	(-0.547)	(0.660)	(-0.058)	(-0.454)	(0.949)	(0.265)	(-0.519)	(0.868)	(0.147)
Event CAR[-3,3]	-0.0157	0.0059	-0.0832	-0.0150	0.0078	-0.0796	-0.0181	-0.0045	-0.1011	-0.0173	-0.0024	-0.0971
	(-0.491)	(0.105)	(-1.213)	(-0.476)	(0.142)	(-1.183)	(-0.518)	(-0.070)	(-1.309)	(-0.503)	(-0.039)	(-1.288)
Notches	0.0056 **	0.0122 ***	0.0052	0.0053 **	0.0116 ***	0.0040	0.0053 *	0.0113 ***	0.0036	0.0051 *	0.0107 ***	0.0024
	(2.159)	(3.977)	(0.883)	(2.085)	(3.807)	(0.660)	(1.938)	(3.743)	(0.610)	(1.881)	(3.572)	(0.408)
Ln (TA)	-0.0019	-0.0142 ***	-0.0334 ***	0.0020	-0.0035	-0.0127 **	-0.0019	-0.0142 ***	-0.0335 ***	0.0019	-0.0040	-0.0134 **
	(-0.566)	(-3.616)	(-5.034)	(0.832)	(-0.755)	(-2.164)	(-0.568)	(-3.649)	(-5.072)	(0.816)	(-0.891)	(-2.371)
SGA	0.0234 **	0.0358 *	0.0633 ***	0.0263 **	0.0435 **	0.0783 ***	0.0229 **	0.0337 **	0.0597 ***	0.0257 **	0.0411 **	0.0742 ***
	(2.096)	(1.943)	(3.096)	(2.261)	(2.250)	(3.386)	(2.130)	(1.991)	(2.784)	(2.285)	(2.312)	(3.036)
PPE	0.0029	-0.0702	-0.0284	0.0052	-0.0640	-0.0164	0.0020	-0.0743	-0.0355	0.0043	-0.0683	-0.0237
	(0.064)	(-1.145)	(-0.537)	(0.112)	(-1.049)	(-0.315)	(0.043)	(-1.249)	(-0.692)	(0.091)	(-1.152)	(-0.469)
MTB	-0.0604 ***	-0.0957 ***	-0.1319 ***	-0.0583 ***	-0.0899 ***	-0.1206 ***	-0.0605 ***	-0.0960 ***	-0.1324 ***	-0.0584 ***	-0.0904 ***	-0.1214 ***
	(-14.103)	(-11.319)	(-9.195)	(-17.378)	(-11.078)	(-10.123)	(-14.194)	(-11.405)	(-9.303)	(-17.792)	(-11.363)	(-10.468)
ROA	0.2467 ***	0.3604 ***	0.6268 ***	0.2427 ***	0.3497 ***	0.6060 ***	0.2453 ***	0.3544 ***	0.6166 ***	0.2415 ***	0.3443 ***	0.5968 ***
	(5.846)	(4.988)	(8.721)	(5.598)	(4.663)	(7.414)	(5.781)	(5.153)	(8.284)	(5.555)	(4.801)	(7.183)
Altman-Z	0.0108 ***	0.0170 ***	0.0145 ***	0.0110 ***	0.0175 ***	0.0156 ***	0.0108 ***	0.0169 ***	0.0145 ***	0.0110 ***	0.0175 ***	0.0155 ***
	(14.788)	(6.650)	(5.278)	(14.748)	(8.088)	(7.084)	(14.650)	(6.744)	(5.430)	(14.774)	(8.114)	(7.186)
RD-Ind.	0.0167 ***	0.0175 **	0.0179 *	0.0177 ***	0.0200 ***	0.0229 **	0.0166 ***	0.0167 **	0.0166	0.0175 ***	0.0192 **	0.0214 **
	(2.694)	(2.420)	(1.808)	(2.806)	(2.759)	(2.245)	(2.661)	(2.227)	(1.608)	(2.774)	(2.553)	(2.025)
β_0: Constant	0.0128	0.0449 *	0.0447	0.0142	0.0485 *	0.0518 *	0.0133	0.0467 *	0.0480 *	0.0145	0.0502 *	0.0547 *
	(0.790)	(1.716)	(1.615)	(0.847)	(1.840)	(1.817)	(0.822)	(1.755)	(1.659)	(0.874)	(1.864)	(1.832)
Adjusted - R^2	0.114	0.129	0.102	0.115	0.133	0.110	0.115	0.134	0.111	0.116	0.138	0.118

Table 7: Portfolio Return Regressions

Table reports results of seemingly unrelated regressions (*SUR*) of daily excess returns on contemporaneous Fama-French and momentum factors with fixed effects for year and industry using Fama and French 17 industry classifications and robust standard errors clustered by industries.

$$R_{it} - R_{ft} = \alpha_p + \beta_{RMRF,p}(R_{Mt} - R_{ft}) + \beta_{SMB,p}SMB_t + \beta_{HML,p}HML_t + \beta_{UMD,p}UMD_t + \beta_{Rated,p}S\&P\ Rated_i + \beta_{IG,p}Investment\ \ Grade_i + \beta_Z Z_i + \varepsilon_{it}$$

where i are the firms in portfolio p and Z_i denote firm characteristics *Ln(TA)*, *SGA*, *PPE*, *MTB*, *ROA*, *Altman-Z*, and *R&D*. Our return series starts 4-days after the announcement date and continues for 252 trading days. Peers are stratified into quartile portfolio sorted on return synchronicity (Panel A), earnings transparency (Panel B), and summed ranks on return synchronicity and earnings transparency in Panel C. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the event firm in the announcement year. *t*-statistics are presented in parentheses. *F*-statistics from joint coefficient tests are present in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 7: Portfolio Return Regressions (Cont.)

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{RMRF,i}(R_{M,t} - R_{f,t}) + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{UMD,i}UMD_t + \beta_{Rated,i}Rated_t + \varepsilon_{i,t}$$

	Panel A: Price Synchronicity					**Panel B: Earnings Transparency**				
	(1)	**(2)**	**(3)**	**(4)**	**(4) - (1)**	**(1)**	**(2)**	**(3)**	**(4)**	**(4) - (1)**
α_p	-0.0000	0.0001	0.0002 **	0.0004 ***	0.0004	0.0001	-0.0000	-0.0002 *	0.0005 ***	0.0004
t-statistic	(-0.426)	(1.209)	(2.565)	(3.224)		(0.613)	(-0.003)	(-1.778)	(9.991)	
F-test					[11.27] ***					[5.99] **
β_{RMRF}	1.0599 ***	0.9964 ***	0.7860 ***	0.4908 ***	-0.5691	0.8795 ***	0.8709 ***	0.8280 ***	0.8355 ***	-0.044
t-statistic	(36.175)	(29.771)	(16.323)	(12.282)		(43.614)	(41.415)	(14.863)	(33.092)	
F-test					[91.3] ***					[1.71]
β_{SMB}	0.6568 ***	0.7698 ***	0.6187 ***	0.3892 ***	-0.2676	0.6456 ***	0.6336 ***	0.6288 ***	0.5837 ***	-0.0619
t-statistic	(7.340)	(9.308)	(9.933)	(12.637)		(20.715)	(7.213)	(9.450)	(7.729)	
F-test					[15.92] ***					[1.54]
β_{HML}	-0.1343	0.1030	0.2186 *	0.1293 *	0.2636	-0.0174	0.1472	-0.1076	0.1962	0.2136
t-statistic	(-0.501)	(0.632)	(1.840)	(1.669)		(-0.169)	(0.995)	(-0.506)	(1.466)	
F-test					[1.86]					[21.16] ***
β_{UMD}	-0.2254 *	-0.0806	-0.0337	-0.0362	0.1892	-0.1248 **	-0.0254	-0.1616	-0.0789	0.0459
t-statistic	(-1.917)	(-0.995)	(-0.622)	(-0.686)		(-2.453)	(-0.280)	(-1.504)	(-1.231)	
F-test					[7.97] **					[2.48]
β_{Rated}	0.0003 **	0.0001	0.0006 ***	0.0009 **	0.0006	0.0000	0.0006 ***	0.0008 ***	0.0001	0.0001
t-statistic	(1.996)	(1.219)	(4.973)	(2.416)		(0.101)	(3.083)	(3.425)	(0.711)	
F-test					[3.51] *					[0.04]
$\beta_{Investment}$	0.0000	-0.0001	-0.0007 ***	-0.0012 ***	-0.0012	-0.0000	-0.0006 ***	0.0000	-0.0004 *	-0.0004
t-statistic	(0.172)	(-1.035)	(-6.908)	(-3.848)		(-0.084)	(-2.636)	(0.156)	(-1.863)	
F-test					[16.96] ***					[2.27]
Adjusted - R^2					0.123					0.115

Table 7: Portfolio Return Regressions (Cont.)

	Panel C: Combined				
	(1)	(2)	(3)	(4)	(4) - (1)
α_p	-0.0001 **	0.0000	0.0001	0.0007 ***	0.0008
t-statistic	(-2.405)	(0.456)	(1.035)	(12.006)	
F-test					[152.36] ***
β_{RMRF}	1.0534 ***	0.8856 ***	0.7967 ***	0.6073 ***	-0.4461
t-statistic	(33.884)	(33.278)	(28.337)	(14.152)	
F-test					[78.33] ***
β_{SMB}	0.7245 ***	0.6543 ***	0.5867 ***	0.4699 ***	-0.2546
t-statistic	(8.000)	(9.473)	(10.100)	(11.795)	
F-test					[17.91] ***
β_{HML}	-0.0474	0.0906	0.1335	0.1432	0.1906
t-statistic	(-0.195)	(0.557)	(1.022)	(1.604)	
F-test					[1.45]
β_{UMD}	-0.1887 *	-0.0943	-0.0645	-0.0302	0.1585
t-statistic	(-1.743)	(-1.271)	(-0.957)	(-0.539)	
F-test					[8.36] **
β_{Rated}	0.0003 ***	0.0005 ***	0.0005 **	0.0005	0.0002
t-statistic	(2.775)	(3.241)	(2.463)	(1.230)	
F-test					[0.22]
$\beta_{Investment}$	-0.0000	-0.0002	-0.0005 ***	-0.0010 ***	-0.001
t-statistic	(-0.131)	(-0.990)	(-2.844)	(-2.607)	
F-test					[5.38] **
Adjusted - R^2					0.119

Table 7: Portfolio Return Regressions (Cont.)

	Return Synchronicity	*Earnings Transparency*	*Return Synchronicity and Earnings Transparency*
***Event CAR*[-3,3]**	-0.0011 **	-0.0011 **	-0.0010 **
	(-2.562)	(-2.276)	(-2.450)
Notches	-0.0000	0.0000	-0.0000
	(-0.751)	(0.131)	(-0.674)
Ln(TA)	-0.0001 ***	-0.0002 ***	-0.0001 ***
	(-3.122)	(-5.617)	(-4.045)
SGA	0.0004 ***	0.0003 ***	0.0003 ***
	(4.086)	(3.665)	(4.641)
PPE	-0.0001	-0.0002	-0.0001
	(-0.526)	(-1.558)	(-0.629)
MTB	-0.0006 ***	-0.0006 ***	-0.0006 ***
	(-11.159)	(-13.625)	(-13.578)
ROA	0.0022 ***	0.0021 ***	0.0021 ***
	(10.509)	(7.623)	(9.538)
Altman-Z	0.0001 ***	0.0000 ***	0.0001 ***
	(5.742)	(3.495)	(4.733)
R&D	0.0001	0.0001	0.0001
	(0.544)	(0.421)	(0.536)
Adjusted R^2	0.096	0.090	0.093

Table 8: Future Changes in Profitability

Table reports results of OLS cross-sectional regressions of the changes in profitability of peer firms with fixed effects for year and industry using Fama and French 17 industry classifications and robust standard errors clustered by industries. Peers are firms in *Compustat* that operate in the same three-digit SIC code as the event firm in the announcement year. *ROA* is calculated as EBIT scaled by Total Revenue. *Profit* is net income scaled by Total Revenue. Changes in *ROA*, *Profit*, and *EPS* are computed from fiscal year preceding and following the announcement year. Event Firm *CAR[*-3,3], Notches, *Ln(TA)*, *SGA*, *PPE*, *MTB*, *ROA*, and *Altman-Z* are demeaned by the cross-sectional average. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 7: Portfolio Return Regressions (Cont.)

	Price - Synchronicity			Earnings - Transparency			Full Model		
	ΔROA [-1,1]	ΔProfit [-1,1]	ΔEPS [-1,1]	ΔROA [-1,1]	ΔProfit [-1,1]	ΔEPS [-1,1]	ΔROA [-1,1]	ΔProfit [-1,1]	ΔEPS [-1,1]
β_1: P - Synchronicity	-0.0693 ***	-0.1262 ***	-0.6314 **				-0.0679 ***	-0.1232 ***	-0.6024 **
	(-3.060)	(-5.413)	(-2.249)				(-3.055)	(-5.608)	(-2.299)
β_2: E - Transparency				0.0491 ***	0.1032 **	0.9668 ***	0.0462 **	0.0980 **	0.9411 ***
				(2.684)	(2.356)	(2.693)	(2.442)	(2.271)	(2.664)
S&P Rated (1 if yes)	0.0019	0.0007	-0.0338	0.0017	0.0005	-0.0345	0.0019	0.0008	-0.0333
	(0.307)	(0.079)	(-0.486)	(0.278)	(0.055)	(-0.480)	(0.321)	(0.088)	(-0.485)
Investment Rated	-0.0017	0.0071	0.0479	-0.0007	0.0090	0.0611	-0.0013	0.0079	0.0560
	(-0.302)	(0.611)	(0.426)	(-0.126)	(0.740)	(0.545)	(-0.234)	(0.708)	(0.493)
Event CAR[-3,3]	-0.0239 *	-0.0728 *	-0.3578 ***	-0.0264 **	-0.0780 **	-0.4002 ***	-0.0256 *	-0.0763 **	-0.3923 ***
	(-1.749)	(-1.894)	(-3.980)	(-2.026)	(-2.131)	(-3.899)	(-1.920)	(-2.050)	(-3.949)
Notches	-0.0024 *	0.0005	0.0178	-0.0024 *	0.0005	0.0167	-0.0025 **	0.0002	0.0153
	(-1.890)	(0.177)	(0.935)	(-1.888)	(0.189)	(0.896)	(-1.974)	(0.083)	(0.819)
Ln (TA)	0.0018	-0.0040 *	0.0310 ***	-0.0015 *	-0.0100 ***	0.0010	0.0017	-0.0041 *	0.0295 ***
	(0.953)	(-1.686)	(2.752)	(-1.705)	(-3.817)	(0.054)	(0.929)	(-1.791)	(2.613)
SGA	-0.0113	-0.0445	0.1304	-0.0145 **	-0.0505	0.0966	-0.0117 *	-0.0456	0.1204
	(-1.627)	(-1.000)	(0.986)	(-2.254)	(-1.148)	(0.798)	(-1.752)	(-1.035)	(0.953)
PPE	-0.0073	0.0750 *	0.0056	-0.0100	0.0698 *	-0.0247	-0.0079	0.0737 *	-0.0063
	(-0.580)	(1.894)	(0.045)	(-0.821)	(1.732)	(-0.191)	(-0.621)	(1.864)	(-0.052)
MTB	0.0045 ***	0.0334 ***	0.0788 ***	0.0027 **	0.0302 ***	0.0624 ***	0.0044 ***	0.0332 ***	0.0774 ***
	(3.376)	(3.326)	(2.917)	(2.362)	(2.970)	(2.656)	(3.303)	(3.307)	(2.908)
ROA	0.0717 ***	-0.0565	0.4356	0.0734 **	-0.0536	0.4397	0.0706 ***	-0.0587	0.4142
	(2.612)	(-0.779)	(1.207)	(2.536)	(-0.722)	(1.233)	(2.612)	(-0.820)	(1.187)
Altman-Z	-0.0028 ***	-0.0108 ***	-0.0347 ***	-0.0030 ***	-0.0111 ***	-0.0365 ***	-0.0028 ***	-0.0108 ***	-0.0349 ***
	(-12.441)	(-15.649)	(-8.639)	(-19.482)	(-18.873)	(-6.791)	(-12.319)	(-15.675)	(-8.944)
RD-Ind.	0.0029	0.0073	0.0032	0.0021	0.0058	-0.0047	0.0028	0.0071	0.0017
	(1.015)	(0.774)	(0.044)	(0.692)	(0.607)	(-0.065)	(0.994)	(0.763)	(0.024)
β_0: Constant	0.0129	0.0730 ***	0.5525 ***	0.0119	0.0712 ***	0.5459 ***	0.0131	0.0734 ***	0.5568 ***
	(1.545)	(5.042)	(4.105)	(1.469)	(4.909)	(4.097)	(1.569)	(4.986)	(4.152)
Adjusted - R^2	0.058	0.051	0.054	0.056	0.050	0.056	0.060	0.051	0.058

Appendix A: Variable Definitions

Variable	Definition
P-Trans	Price synchronicity transparency: P-Trans is calculated as the difference in the R^2 from a Carhart (1997) four-factor model estimated over the period 282 to 30 days prior to announcement from the median R^2 of all peers at the event.
E-Trans	Earnings transparency is calculated following Barth et al. (2013).
S&P Rated	Indicator variable which takes a value of 1 if the peer firm is rated at the fiscal year end preceding the event year and 0 otherwise.
Investment Grade	Indicator variable which takes a value of 1 if the peer firm is rated investment grade at the fiscal year end preceding the event year and 0 otherwise.
Non-Rival	Firms in Compustat which operate in the same three-digit SIC code as the event firm in the year of the announcement excluding rivals.
Event CAR[-3,3]	The cumulative abnormal return to the event firm in the period 3-days before the event to 3-days after. Abnormal returns are calculated using a Carhart (1997) four-factor model estimated over the period 282 to 30 days prior to announcement.
Notches	The number of rating levels the event firm moves, e.g., Notches would take a value of 2 for a move from BBB- to BB.
***Ln*(TA)**	The natural log of book total assets.
SGA	Selling, general, and administrative expense scaled by total revenue.
PPE	Net property, plant, and equipment scaled by total book assets.
MTB	Book total assets minus total equity plus market capitalization all divided by book total assets.
ROA	EBIT divided by book total assets.
Altman-Z	=1.2*(Current Assets-Current Liabilities)/Book Total Assets+1.4*Retained Earnings/Book Total Assets+3.3*EBIT/Book Total Assets+0.6*(Shares Outstanding*Price per Share)/Total Liabilities+0.999*Total Revenue/Book Total Assets
RD-Ind.	An indicator which takes a value of 1 if the firm has R&D expenses greater than zero and 0 otherwise.
ΔROA [-1,1]	The change in ROA from the fiscal year end preceeding the announcement year to the fiscal year end following the announcement year, e.g., for an event which occurs in 2003, ΔROA would measure the change from fiscal year end 2002 to fiscal year end 2004.
ΔProfit [-1,1]	The change in profit margin from the fiscal year end preceeding the announcement year to the fiscal year end following the announcement year, e.g., for an event which occurs in 2003, ΔProfit would measure the change from fiscal year end 2002 to fiscal year end 2004.
ΔEPS [-1,1]	The change in earnings per shares outstanding from the fiscal year end preceeding the announcement year to the fiscal year end following the announcement year, e.g., for an event which occurs in 2003, ΔEPS would measure the change from fiscal year end 2002 to fiscal year end 2004.

Appendix B: Event Sample Selection

This table outlines the sample selection procedure. The full sample consists of all *S&P* credit rating downgrades from investment to speculative grade in the sample period January 1, 2000 through December 31, 2010 compiled from Bloomberg Data Services.

Full Sample		257
Less		
Same Industry within 15-days	12	
Same Firm within 1-year	3	
Merger Announcement ±22 trading days	28	
Insufficient CRSP Data	36	
Infrequently Traded Equity Pre-Event (<90% of trading days)	4	
Less Than 1-year of Trading Data Post-Event	25	
Insufficient Compustat Data	10	
Events with Stock Price Below $5	6	
Final Sample		133

III. Essay 2: Credit Rating Initiations, Liquidity, and Seasoned Equity Offerings[15]

Wayne Y. Lee and Garrett A. McBrayer

A. Abstract

Prior literature documents economically significant costs in equity trading that result from informational asymmetry. Asymmetries lead to adverse selection costs being reflected in the price patterns and trading behavior of market participants in the secondary markets for equity. Mechanisms which reduce asymmetries then reduce the costs of transacting by ameliorating the costs to doing so. In this study, we use a sample of credit rating initiations, the first-time a firm obtains a long-term issuer rating from *Standard and Poor's*, to examine the effects that becoming rated has on secondary market equity liquidity. We find that the firms who decide to become rated see an improvement in secondary market liquidity regardless of the specific measure we use to measure liquidity. Measures of changes in Amihud (2002) liquidity and volume show an improvement over a match set of control firms of 10.82% and 7.4% in the period 90-days before the rating to 90-days after. Ask-bid spread, the costs to transacting, falls by 3.56% more for newly-rated firms than for control firms. Finally, we show how managers take advantage of the increased liquidity through the issuance of seasoned equity offerings. Relative to the control group, newly-rated firms are more likely to issue and suffer less in terms of valuation for doing so.

JEL Classification: G12, G14, G24

Keywords: credit ratings, information asymmetry, adverse selection, liquidity, seasoned equity offerings

[15] We wish to thank seminar participants at the University of Arkansas for their valuable comments and suggestions. All errors remain our own.

B. Introduction

Informational asymmetries in financial markets regarding to the valuation of a firm's assets have direct effects on the risk inherent in the firm's debt and equity. Prior literature documents a positive and significant relation between measures of adverse selection in equity-markets and the trade behavior exhibited by market participants when information is uncertain.[16] In the presence of informational asymmetries, Copeland and Galai (1983) model this process as it pertains to the bid-ask spreads of market makers when dealing with two different types of traders who trade with distinct motives, i.e., those possessing special information and those trading for liquidity purposes. Using a framework wherein the cost of supplying quotes is viewed as writing a put and call option to an informed trader, they show that the bid-ask spread is a positive function of asset volatility and a negative function of market depth, or liquidity. In other words, the bid-ask spread accounts for the fact that the marker maker loses when trading to an information-motivated trader. The challenge for the market maker then becomes identifying one type from another, or, protecting herself from losses arising from trading with informed traders. The challenge for broader market efficiency is to alleviate (at least to the extent possible) the informational asymmetries that exist.

Credit rating agencies play a crucial role to this end by alleviating the informational asymmetries that exist between firms and market participants. To assess the creditworthiness of a firm, credit rating agencies rely on their access to material, non-public information about the firm's prospects. In fact, this access to information was deemed essential enough to the efficient functioning of markets that it was protected by government legislation in 2000. Regulation Fair Disclosure Act (Reg FD) preserved the selective disclosure of material, non-public information

[16] See, for example, Flannery, Kwan, and Nimalendran (2013 and 2004), Clarke, Fee, and Thomas (2004), Krinsky and Lee (1996), and Singh, Zaman, and Krishnamutri (1994).

to nationally recognized statistical rating organizations and credit ratings agencies.[17] The benefits of a credit rating extend beyond the identification, or validation, that occurs at the initial rating. Credit rating agencies act as monitors bearing the threat of adverse rating changes as a mechanism to ensure firm compliance with bond indentures (Boot, Milbourn, and Schmeits, 2006). However, despite the certification and monitoring effects of rating agencies, the literature on measures of adverse selection in equity markets and credit ratings have developed largely independently.

Odders-White and Ready (2006) and He, Wang, and Wei (2010) are among the few studies to examine these two bodies in conjunction. In their study, Odders-White and Ready model the relation between firm credit ratings and adverse selection in equity market trading. Their model suggests that that firms that have a higher probability of large changes in firm value should have both poorer credit ratings and higher adverse selection costs to trading in their equity. They test this result empirically using Trade and Quote (TAQ) data and find that credit ratings changes and measures of adverse selection costs are negatively related. That is, as credit ratings degrade the adverse selection costs of trading the firm's equity increase. The findings of Odders-White and Ready suggest that credit ratings and asymmetric information are inversely related, i.e., as ratings improve (degrade) the problem of asymmetric information is reduced (made greater). More directly, He et al. (2010) show that rating changes and information asymmetry are inversely related. As ratings go up (down), measures of information asymmetry fall (rise).

However, Odders-White and Ready never make a claim regarding the causality of the relationship because their dataset limits their ability to test the direction of the relationship.

[17] Regulation Fair Disclosure [Rule 100(b)(2)].

Recognizing this limitation, they examine the extent to which one predicts the other. They find support that credit ratings changes are predictive, to some extent, of changes in adverse selection. This results suggests that the rating change is a casual factor affecting the degree of asymmetric information.

In this study, we contribute to the findings of Odders-White and Ready by examining the effects on the information environment and trading behavior of a firm's equity when the firm becomes rated for the first time. More specifically, we use a dataset which uniquely identifies 1,182 first-time *Standard and Poor's* long-term issuer credit ratings to examine the effects that becoming rated has on the liquidity with which the firm's equity trades. Our study focuses on long-term issuer credit ratings due to fact that they reflect, according to *S&P's* documentation, the "...overall obligor's capacity and willingness to meet its financial commitments as they come due" and the rating "…does not take into account the specific nature or provisions of any particular obligation." [18] *S&P's* long-term issuer credit ratings reflect the overall creditworthiness and financial condition of the firm and, as such, ameliorate, to a certain extent, the informational asymmetries that exist pertinent to the asset values of the rated firm. Long-term issuer ratings offer greater reductions in adverse selection costs to transacting in a firm's equity than ratings pertinent to a given issue.

We use three previously developed measures of equity liquidity (i.e., *Amihud Liquidity* (2002), *Volume*, and *Ask-Bid Spread*) to examine the extent to which the initiation of a new credit rating induces changes in equity market liquidity. For each of our three measures, we calculate a rolling average for a period of time pre- and post-new credit rating, excluding the 21-day window centered on the credit rating issue date, and measure the percentage change in the

[18] See *Standard and Poor's* Corporate Rating Criteria (2008).

respective measure.[19] To control for contemporaneous market movements and for contemporaneous changes in liquidity measures for similar firms, we propensity score match our event firms to an unrated, control group.

Our main findings can be briefly summarized as follows. First, we document a statistically significant increase in secondary market equity liquidity following the initiation of a new credit rating. For our event firms, measures of *Amihud Liquidity* and *Volume* increase by an average 47.749% and 29.54% in the 200 trading days surrounding the credit rating initiation, respectively. *Ask-Bid Spread* falls by an average -4.80% over the same time period. Second, when our event firm changes are compared to our control group, all measures show improved liquidity for the firms who obtained a credit rating relative to the unrated control group. These differences are significant across all comparisons in liquidity. In a multivariate framework, these differences are significant at better than the 5% regardless of the liquidity measure used for all specifications. Our results suggest that the credit rating itself reduces information asymmetry thus leading to an improvement in secondary market liquidity surrounding the new rating event. The question then becomes what, if any, are the long-term implications? And, what effect, if any, does this have on the financing behavior of the firm?

We examine the long-term, non-transitory effects of being credit rated on equity liquidity by looking at the seasoned equity offering (SEO) activity of our two sets of firms, event and control. If the effects of becoming credit rated are transitory, then we should not expect any differences in the SEO activity of our two groups. In our sample, however, firms which obtain a credit rating are 178.84% more likely to issue a SEO following the credit rating event than our control firms, 36.89% of our event firms issue a SEO while only 13.23% of our control firms

[19] Our results are robust to alternate definitions of the event window, i.e., 11-day and 5-day.

issue. To ensure this result is not driven by mechanical adjustments to an optimal capital structure post-rating initiation, we control for the change in firm leverage from initiation date to SEO date (Faulkender and Peterson, 2006). After controlling for the change in firm leverage and other firm characteristics, we find that credit rating initiation firms are 21.75% more likely to issue than the firms in our control group.

Finally, the risk-adjusted, cumulative abnormal returns to our event firms are less negative surrounding the SEO issue date. This result supports the findings of Butler, Grullon, and Weston (2005) who show that market liquidity is a significant determinant of the costs of raising external capital. Overall, the effects of becoming credit rated on equity liquidity are non-transitory and increase the likelihood that a firm issues seasoned equity while reducing the costs for doing so.

Collectively, our results provide support to prior literature documenting the economic importance of credit ratings.[20] The identification, certification, and validation that occur with a new credit rating affect the information environment with which the newly rated firm's equity trades. Our findings suggests that credit ratings serve to resolve information asymmetry and improve market liquidity.

The remaining sections of this paper are organized as follows. Section 2 reviews the related literature and summarizes our hypotheses. Section 3 describes the data used for our analysis and our empirical methodology. Section 4 discusses the results of tests examining the change in equity liquidity surrounding credit rating initiations. Empirical results on the long-term effects of credit ratings on SEOs are presented in Section 5. Section 6 concludes.

C. Concept Development and Related Literature

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[20] See, for example, Holthausen and Leftwich (1986), Dichev and Piotroski (2001), and Lee, and McBrayer (2015).

The purpose of our study is to examine the impacts that credit rating initiations have on the environment in which the firm's equity trades. More precisely, we seek to test for the relation between new credit ratings and measures of equity market liquidity and to examine the extent to which this relation affects the financing behavior of the firm. As such, this paper relates two strands of literature. The first examines the informativeness of credit ratings and their relation to equity market liquidity. And the second, the external financing implications of equity market liquidity.

1. Credit Ratings and Liquidity

Prior literature documents significant, long-term valuation consequences of the credit rating changes. Holthausen and Leftwich (1986) find significant negative abnormal equity returns surrounding inter-class downgrades, i.e., downgrades across rating classes, on the magnitude of -2.66% over a two-day window ending one-day after the event date but little effect of intra-class downgrades.[21] The effects appear to be non-transitory. Dichev and Piotroski (2001) find abnormal returns to downgraded firms over the first-year following the downgrade on the order of -10% to -14%. They show that the effects are strongest for firms with speculative grade debt and small firms where investor interest is relatively low. The findings of Holthausen and Leftwich (1996) and Dichev and Piotroski (2001) suggest that credit rating changes provide new information to markets. Ederington and Goh (1998) examine the earnings of firms who undergo a credit rating change, upgrade or downgrade, to examine the impact on accounting profits for evidence of real changes in economic performance. Their results show that downgrades are preceded by declines in earnings thus forecast falling earnings post downgrade. This results suggests that changes in credit ratings are indicative of changes in the long-term financial prospects and credit worthiness of downgraded firms. In markets characterized by information

[21] For example, an inter-class downgrade is a change from *AA* to BBB^+ while an intra-class downgrades is a change from *AA* to AA^-.

asymmetries, credit rating agencies play a crucial role in apportioning the risks between market participants.

Equity market adverse selection risk engenders uncertainty in asset valuation. To the extent that information is asymmetric, measures of adverse selection risk based on trade behavior capture the adverse selection costs in financial markets and the liquidity with which assets trade.[22] The liquidity with which a given asset trades reflects the adverse selection costs associated with that asset. Mechanisms which ameliorate the information asymmetry problem should then serve to mitigate the adverse selection costs to trading. Credit ratings, levels and changes, act as just such a mechanism.

The unique access to material, non-public information granted to credit rating agencies in Reg FD combined with the fact that rating agencies act as monitors post-rating (Boot, Milbourn, and Schmeits, 2006) suggests that credit rating changes contain, in part, information which affects the information asymmetry of the asset in question. Odders-White and Ready (2006) explore the correlation between credit rating changes and measures of equity market liquidity. Using trade level data, they find that measures of adverse selection are larger when credit ratings are poorer. He et al. (2010) extend the result of Odders-White and Ready (2006) by examining the relation between changes in credit ratings and contemporaneous changes in information asymmetry. He et al. (2010) provide evidence that credit rating changes are inversely related to measures of information asymmetry. Specifically, they show that when firms experience an upgrade (downgrade), its stock information asymmetry and its analyst forecast dispersion are significantly reduced (increased).

[22] Glosten and Milgrom (1985), Amihud and Mendelson (1986 and 1989), Brennan and Subrahmanyam (1996), Eleswarapu (1997), Brennan, Chordia, and Subrahmanyam (1998), and Amihud (2002), among others, provide evidence that liquidity is priced in the cross-section of stock returns.

The results of Odders-White and Ready (2006) and He et al. (2010) indicate that credit ratings and credit rating changes are associated with changes in information asymmetry. One limitation of the prior studies in this area, however, is that they say little about the causality of the relationship. In fact, Odders-White and Ready (2006) find that changes in measures of adverse selection are predictive of future changes in credit ratings. Regardless, the rationale for why credit rating initiations (instances of new credit ratings) might affect information asymmetry and thus liquidity is straight forward. The findings of prior literature in this are point to significant market reactions to credit ratings changes and a robust relation between credit ratings, credit rating changes, and equity liquidity. Further, credit ratings agencies are privy to material, non-public information about the firms they rate. The distinct access to information afforded credit ratings agencies uniquely positions them to be able to signal to markets about the firm's quality through the credit rating. In a market characterized by informational asymmetries, credit rating initiations should serve to reduce uncertainty either through the revelation of new information or through the certification or validation of existing beliefs.

2. Liquidity and Seasoned Equity Offerings

The long-term implications that being rated has on equity liquidity less clear. To our knowledge, no study has examined the non-transitory effects that credit ratings or credit rating changes have on equity liquidity. However, literature on the relation between liquidity and SEO activity provides a natural setting for which to explore the permanent effects that becoming rated may have on equity liquidity.

Butler, Grullon, and Weston (2005) provide evidence that stock market liquidity is an important determinant of the cost of SEOs. By examining the connection between floatation costs on SEOs and the secondary market liquidity of the firm's existing shares, they find that the cost reduction in banker's fees is about 101 basis points or 21% of the average investment banking fees for firms in their sample with the most liquid equity relative to firms with the least liquid equity. Their result is significant in that it contributes to the debate on whether a firm has any interest in the liquidity with which its equity trades in the secondary market. Firm value is affected by secondary market liquidity in that managers, seeking to maximize firm value, should issue SEOs when liquidity costs are lowest. Lin and Wu (2013) examine this claim by investigating the extent to which the market timing of SEOs can be explained by the dynamics of liquidity risk. Using asset-pricing portfolio regressions, their study identifies a robust relationship between liquidity declines and SEO filing activity. Firms file for SEOs when their liquidity risk for doing so falls to its lowest point in the period preceding the filing date and then rises ex-post.

Managers time SEO filings, in part, when the costs to doing so are favorable. Among the cost concerns of the manager, are the liquidity costs which result from asymmetric information. To the extent that credit rating initiations reduce asymmetries and thus affect equity market liquidity and liquidity costs, the results of Butler et al. (2005) and Lin and Wu (2013) suggest that SEO activity should be different for firms following their initial credit rating than for similar firms who choose not to become rated.

D. Data Description, Summary Statistics, and Methodology

In this section, we discuss our sample selection procedure and explain the matching strategy we employ to control for contemporaneous changes in secondary market liquidity driven by market movements or for like firms.

1. Data Description

Our initial sample consists of a universe of long-term, *S&P* issuer credit rating initiations consisting, 2,270 observations, obtained from *Bloomberg Data Services* over the period January 1^{st}, 1991 through December 31^{st}, 2010. We start our sample in 1991 due to data availability from *Bloomberg* and end our sample in 2010 to avoid truncation in our SEO testing. To be included in our final sample, each observation must meet the following criteria: the firm must be followed by both *CRSP* and *Compustat* databases; the firm must have been tracked in *CRSP* for at least 252 trading days prior to the rating initiation and at least 100 trading days post; and, the firm must have non-missing values for total book assets and total revenue in *Compustat*. These criteria generate a final sample of 1,182 credit rating initiations.

In addition to the credit rating initiations data, we collect data on the universe of 11,561 SEOs from Thomson Reuters' Securities Data Company (SDC) Global New Issues database over the period January 1^{st}, 1991, through December 31^{st}, 2010. Following Butler et al. (2005) and Lin and Wu (2013) we require that our sample of SEOs meet the following requirements: the size of the SEOs is at least 5% of the existing, outstanding equity of the SEO firm; the offering is a firm commitment; and, the offering is not a shelf registration.[23]

To measure the changes in equity liquidity surrounding a credit rating initiation we construct the following three measures of market liquidity from CRSP data: *Amihud Liquidity*, *Volume*, and *Ask-Bid Spread*. We construct *Amihud Liquidity* following Amihud (2002), i.e., it is the absolute value of the daily return over the daily dollar volume, except that we use the reciprocal of this value for the purposes of interpretation so that positive changes reflect a liquidity increase. Amihud (2002) argues that this measure can be interpreted as the daily price

[23] All of our results are qualitatively unchanged to changes in the size requirement, e.g., moving from 5% to 10%.

response associated with one dollar of trading volume, thus serving as a rough measure of price impact. Following Brennan et al. (1998), we compute *Volume* as the daily trading volume as reported by *CRSP*. Positive values of *Volume* reflect increases in equity liquidity. Finally, we, and consistent with Odders-White and Ready (2006), we construct *Ask-Bid Spread* as the difference between the daily closing ask price and bid price. With *Ask-Bid Spread* negative changes reflect a reduction in the costs to transact in the firm's equity, or, increased liquidity.

For all three measures we take an average for a given period of time before and after the initiation, excluding a 21-day window centered on the initiation date, and calculate the percentage change. All measures are averaged for 30, 45, 60, and 90 days before the initiation ending at our initiation window, i.e., 10-days before the initiation date, and again for the same amount of time following the window, i.e., starting 10-days after the initiation date.[24] The percentage change is then calculated for each measure for each time window giving a total of twelve measures, three distinct variables measured over four time-horizons each, of changes in equity liquidity.

2. Summary Statistics

Table 1 reports summary statistics on the distribution of credit rating initiations in our sample by year, by Fama-French (1997) industry, and by the credit rating obtained. As one would expect, credit rating initiations are pro-cyclical. The number of new ratings increase leading into the tech bubble and into the financial crisis and then fall thereafter. The middle columns of Table 1 shows clustering in the distribution of credit rating initiations by industry; initiations cluster in oil, machinery, and finance occur with the greatest frequency.

[24] We construct an initiation window to avoid the potential problem of including information leakage in our pre-event measures. Our results are robust to windows over ±20 days, ±5 days, and to ±3 days.

[Insert Table 1 here]

The right-hand columns of Table 1 detail the distribution of initiations by the credit rating obtained. Most new ratings are speculative grade, 66.7%. Additionally, ratings seem to cluster at rating-class breaks. For instance, the number of ratings increases monotonically moving down from *BBB+* to *BBB-*, moving from 54 to 91, and then falls to 54 at *BB+*.

Table 2 presents descriptive statistics on the changes in equity liquidity surrounding the credit rating initiation date. Panel A details changes in our liquidity measures. The top third of Table 2 panel A presents the changes in *Amihud Liquidity* for 30, 45, 60, and 90-days surrounding the initiation date. The mean percentage change in *Amihud Liquidity* ranges from 32.71% to 35.09% and is significant at better than the 1% level. The data show positive skewness in that mean is greater than the median, however the median change in *Amihud Liquidity* is positive and significant at better than the 1% for three of the four medians and at better than the 5% level for the remainder. *Volume* exhibits a similar pattern to *Amihud Liquidity* in that all four measures are positive and significant at the mean and median and that the means are much more positive than the medians. For *Volume*, all measures are different from zero at better than the 1% level and range from a 21.20% to a 23.16% increase on average. The results of our *Ask-Bid Spread* measure are similar in significance to those previously presented except that the signs are negative reflecting a reduction in the costs to transacting. For all four measures of *Ask-Bid Spread* the means and medians are statistically different from zero at better than the 1% level and range, at the means, from -2.70% to -5.88%.

[Insert Table 2 here]

Panel B of Table 2 examines the association between liquidity and the rating obtained by the newly rated firm. Odders-White and Ready (2006) find that credit ratings are poorer when adverse selection costs are higher. As such, their results suggests that firms who receive higher credit ratings, i.e., ratings indicating greater creditworthiness, should experience greater equity liquidity increases surrounding the rating date. We test this conjecture using a univariate OLS framework wherein we regress *Amihud Liquidity*, *Volume*, and *Ask-Bid Spread* on an ordinal variable, *Rating*, which takes values from 1 (*D* rated) to 22 (*AAA* rated). Higher ratings are associated with larger increases in equity liquidity for all three measures. Coefficient estimates on *Rating* are positive for the specifications using *Amihud Liquidity* and *Volume* and are negative for the specifications using *Ask-Bid Spread*. The coefficient estimates on *Rating* are significant at better than the 1% level for all specifications. The results on *Ask-Bid Spread* are consistent with the findings of Odders-White and Ready (2006). Credit rating initiations are associated with greater reductions in the costs to transacting in the firm's equity for higher rated firms.

3. Methodology

One potential issue not captured by an analysis of liquidity changes for firms surrounding credit rating initiations, particularly when examining non-transitory, long-term changes, is the fact that most measures of equity liquidity are subject to contamination from contemporaneous changes in market-wide liquidity. For instance, the daily volume on the NYSE has increased from roughly 162 million shares per day on January 2nd, 1991 (the start of our sample period) to roughly 807 million shares per day on December 31st, 2010 (the end of our sample period).[25] Any attempt to capture the intermediate to long-term changes in equity liquidity for a given firm also capture broader, market-wide changes. Further confounding the effect is the fact that prior literature finds that changes in liquidity are clustered by industry and by similar firms. Lin and Wu (2013) find that liquidity risk moves in the same direction for both the SEO firms in their

[25] https://www.nyse.com/data/transactions-statistics-data-library

sample as well as the non-issuer control firms. To address the problem of contemporaneous movements in market and/or industry liquidity, we construct a matched sample wherein every credit initiation firm is paired to a propensity score matched control firm.

To propensity score match our initiation firms to their non-initiation peers, we follow the methodology of Faulkender and Peterson (2006) who model the relation between public debt market access and capital structure. Identifying a causal relationship requires that they control for the potential endogeneity problem between being credit rated and a firm's capital structure. In their study, they address this problem through an instrumental variable approach wherein they first model the decision to become credit rated as a function of firm characteristics. Following their methodology, we estimate a probit model over the universe of *Compustat* firms from 1991 through 2010 modeling the decision to become rated. The dependent variable in our probit estimation takes a value of one if the firm is credit rated in a given year and zero otherwise. The independent variables we use are characteristics identified in prior literature to be correlated with capital structure, and, as Faulkender and Peterson show, the presence of a credit rating. *Ln(Total Assets)*, *Ln(1+Age)*, *Leverage*, *Market-to-Book*, *ROS*, *PPE/Assets*, *R&D/Sales*, *Advertising/Sales*, *Tax Rate*, as well as year fixed effects.[26]

We then use our coefficient estimates to calculate a propensity score for each firm-year observation in *Compustat*. Our propensity score matching is then accomplished as follows: for each event firm, we select an unrated, bank-dependent control firm from the fiscal year end preceding the event year whose absolute difference in propensity score from that of the event firm is lowest. We define as "bank-dependent" if the sum of their long-term debt and the current portion of their long-term debt is non-zero. We restrict our universe of control firms to bank-

[26] Variable definitions are presented in Appendix A. Results of this probit estimation are presented in Appendix B.

dependent firms to avoid the problem of modeling a firms decision to use debt, i.e., both our event and control firms have non-zero values for debt reflecting their willingness to use debt financing.[27] In unreported results, we also impose a restriction that the control firms do not become rated for at least three years following the credit rating initiations to prevent contamination of our SEO testing. We dropped this restriction, however, to avoid questions regarding whether or not three years, or any number of years for that matter, were an appropriate length of time. Regardless, assuming that credit ratings affect liquidity and thus SEO activity, removing this restriction biases our results away from finding anything.

The outcome of our matching procedure yields one control firm for every event firm in our credit rating initiation sample. Table 3 present descriptive statistics on the financial characteristics of our subsamples of event and control firms.

[Insert Table 3 here]

At the means, the event firms and control firms are statistically similar in *Ln(Total Assets), Ln*(1+Age), *Leverage*, *Advertising/Sales*, and σ*(Equity Return)*. The only differences are for *Ln(Sales), Market-to-Book*, *ROS*, *PPE/Assets*, and *R&D/Sales*, initiation firms have higher sales, higher growth opportunities, higher profitability, have fewer tangible assets as a percent of total assets, and spend more on R&D as a percent of sales. At the medians, the groups show additional differences in σ*(Equtiy Return)*. Initiation firms have greater prior-year equity volatility, but the difference in *R&D/Sales* is no longer present.

Two results emerge when you compare our results to those of Faulkender and Peterson (2006) which suggest that our procedure yields similar subsamples. First, when comparing firms with public debt market access compared to those without, Faulkender and Peterson find

[27] Our results are robust to this restriction. In fact, the effects are slightly stronger when non-bank dependent firms are included in our control firm subsample.

statistically significant differences at better than the 1% level for every variable presented in Table 3. The fact that we do not provides supporting evidence of the validity of our matching procedure. Secondly, the differences we do identify are in the opposite direction of Faulkender and Peterson. Given that we are simply attempting to identify appropriate control firms and are not interested in the effects of public debt market access on leverage, we take this as additional evidence that our procedure avoids any systematic bias.

E. Empirical Results – Credit Ratings and Liquidity Changes

In this section, we discuss the results from our examination of the effects of credit rating initiations on secondary market equity liquidity.

1. Univariate Results

Table 4 presents descriptive statistics on the changes in equity liquidity surrounding the credit rating initiation date for both our event and control firms and well as statistics on the differences in the two subsamples. The mean and median values for event firms are the same as those presented in Table 2 Panel A and have been discussed previously.

[Insert Table 4 here]

For the control firm subsample, the change in liquidity measures surrounding a credit rating initiation show a statistically significant improvement in equity liquidity for all but the *Ask-Bid* spread measures. Mean and median values are statistically different from zero at better than the 1% level for all eight measures of *Amihud Liquidity* as well as *Volume*. The change in *Ask-Bid* is much weaker being significant for half of the eight measures. The fact that our control firm group exhibits liquidity improvement is consistent with both the findings of Lin and Wu (2013) who find that liquidity risk clusters as well as with an overall improvement of market liquidity over our sample period.[28] We interpret the fact that the liquidity for our control firms improves, albeit to a lesser extent, along with the liquidity to our event firms as further evidence that our propensity score matching routine produces desirable matching results. To control for the clustering and market effects of liquidity changes, we evaluate the differences in the changes in equity liquidity for our two subsamples.

The right-hand column of Table 4 shows the differences in the mean and median value for each liquidity measure across our two groups. The signs of all 24 measures are in the direction we would expect, i.e., the differences are positive for *Amihud Liquidity* and *Volume* and are negative for *Ask-Bid Spread*. We test these differences statistically using *t*-tests on the means and Wilcoxon rank-sum tests on the medians. Statistical tests show that the differences are significant at better than the 5% level for 23 of the 24 comparisons and at better than the 10% for the remainder. The difference is economically meaningful as well. The improvement in equity liquidity for event firms is, when evaluated at the means, 19.34 percentage points greater for *Amihud Liquidity* measures, 11.35 percentage points greater for *Volume* measures, and the cost reduction in *Ask-Bid Spread* is 4.82% more for event firms.

2. Multivariate Results

To account for differences in our subsamples identified in Table 3, we examine the changes in liquidity resulting from credit rating initiations in a multivariate framework. For all measures of equity liquidity changes, we regress the liquidity change on some of the firm and return characteristics identified in prior literature as factors correlated with equity market liquidity. Odder-White and Ready (2006) show that credit rating changes and equity liquidity are related to firm size, leverage, market-to-book, profitability, and prior year asset volatility. We

[28] As previously noted, the volume on the NYSE has increased nearly 400% over the period 1990-2010. https://www.nyse.com/data/transactions-statistics-data-library

include these measures in our liquidity change regressions. In addition, to control for the heterogeneity identified in Table 3 and following Faulkender and Peterson (2006), we also include a measure of asset tangibility, R&D and advertising expenditures, and the natural log of total firm revenue and of one plus firm age. We also include the pre-initiation level of the dependent variable averaged over the same time frame as the dependent variable in the pre-event window. Our primary variable of interest in these equity change regressions if the variable *Event Firm* which is an indicator variable taking a value of one if the firm obtained a credit rating and zero otherwise. All specifications include year and Fama-French 17-industry controls. Robust standard errors are clustered by industry. The results of these tests are presented in Table 5.

[Insert Table 5 here]

The left-hand column of Table 5 presents the results using *Amihud Liquidity* as the dependent variable. For all specifications, the coefficient estimate on *Event Firm* is positive and statistically significant at better than the 5% level. The credit rating is associated, on average, with between an 18.4% and 22.8% increase in equity liquidity for the newly rated firm. Additionally, the intercept, non-rated firms, is only significant in the first two specifications and is insignificant for the remainder suggesting the variation is captured by the included firm characteristics. The results are qualitatively similar for the specifications using *Volume* as the dependent variable. Estimates on *Event Firm* are positive and significant for all four specifications. Credit rating initiations are associated with between an 18.7% and 22.0% increase in equity volume in the 30 to 90-days pre/post initiation for the event firms in our sample. The intercept in our volume change specifications is now significant in the four specifications highlighting the industry clustering and market effects of volume changes.

The right-hand column of Table 5 presents the changes in *Ask-Bid Spread*. Coefficient estimates on *Event Firm* are negative and significant at better than the 5% level for all four specifications. The instance of a new credit rating is associated with between a 4.0% and 5.1% decrease in the cost of transacting in the firm's equity. With the exception of the short-window *Ask-Bid Spread* changes, the intercepts in these specifications are all statistically insignificant. Given that this measure of equity market liquidity change is least susceptible to market movements and changes in industry clusters, we argue that these results are the least contaminated by market and industry clustering effects and best highlight the true cost reduction in transacting associated with credit rating initiations.

Taken together, the initiation of a new, long-term issuer credit rating is associated with statistically and economically significant improvements in equity market liquidity. The event firm benefits in the form of reduced adverse selection risks in transacting in the firm's equity. The question then becomes, to what extent, if any, are managers able to exploit the improvements in liquidity following the credit rating initiation.

F. Empirical Results – Seasoned Equity Offerings

1. Univariate Results

Butler et al. (2005) provide evidence that stock market liquidity is an important determinant of the cost SEOs. Firms with greater (lesser) secondary market liquidity pre-SEO face lower (higher) SEO costs in terms of investment bank fees at SEO. The implication, then, is that managers, seeking to maximize firm value, issue seasoned equity when aftermarket liquidity is high. Lin and Wu (2013) examine this conclusion and find that liquidity risk declines in the 36-months preceding the filing of a new SEO. Liquidity risk seems to be a concern in the decision by firm managers to issue seasoned equity. We extend this literature by investigating various characteristics of SEO activity post-credit rating initiation: the size of SEO issues, the likelihood of a SEO issue, the time to a SEO issue, and the abnormal returns to a SEO issue.

We construct four variables to examine SEO activity/characteristics: 1) *SEO Flag* which takes a value of one if the firm issues a SEO and zero otherwise; 2) *Time to SEO* which counts the number of days from the credit rating initiation date to the SEO issue date; 3) *Issue Size* which scales the issue proceeds by the firm's market capitalization; and, 4) *CAR* which captures the cumulative abnormal return to the issuing firm at the issue date (we measure *CAR* over three time horizons). To construct our abnormal return measures, we use the Carhart (1997) four-factor asset pricing model estimated in the period 282 trading days before the issue date to 30 days before the issue date. Risk-adjusted daily abnormal returns are then the difference between the predicted return for that day and the realized return. We sum the daily abnormal returns around the issue date for three time intervals centered on the date of the issue: ±3 days, ±7 days, and ±10 days. Table 6 presents summary statistics on these measures for our full SEO sample in Panel A, and, by subsample in Panel B.

[Insert Table 6 here]

Of the 2,364 firms in our sample, 580 issue SEOs over our sample period, or, roughly 25.38% of firms. *Time to SEO* is 1205 days at the mean and 630.5 days at the median. The average issue size represents 32.96% of the market capitalization of the issuing firm at the mean, and 18.43% at the median. Consistent with the findings of prior literature, *CAR*s to SEO issues are negative.[29] CARs for two of the three issue windows are negative and statistically significant, i.e., the 7-day and 11-day windows. Over the longer, 21-day window, CARs are negative, but not

[29] Most studies on SEO return patterns focus on the post-issue period to examine the extent, to which, managers issue equity when equity is overvalued. However, Asquith and Mullins (1986), Ritter (1993), Lee (1997), Carlson, Fisher, and Giammarino (2006), and Li and Zhao (2006).

significant. The -1.62% CAR over the 7-day window is quantitatively similar in magnitude to Asquith and Mullins (1986), Ritter (1993), and Lee (1997) who find CARs around SEO filing dates near -2%, on average. SEOs, on average, negatively affect firm valuations.

Panel B of Table 6 splits our sample into the event and control subsamples and examines the differences in our SEO measures. The results suggest that credit rating initiation firms are 178.4% more likely to undergo a SEO post-new rating, 36.89% of event firms issue while only 13.23% of control firms issue. This difference is significant at better than the 1% level. *Time to SEO* is also different across the two groups. For event firms, the mean (median) time to issue is 1259.28 (697) days. In contrast, for control firms the mean (median) time to issue is 1046.51 (473.50) days. The differences are significant at better than the 10% level for the median. *Issue Size* is slightly larger for control firms than for event firms.

One potential issue regarding our investigation into the SEO behavior of the firms in our sample is that SEO behavior may be driven, in part, by the firm's lifecycle. The likelihood of SEO issuance and *Time to SEO* both reflect managerial preferences following the credit rating initiation and could be a function of firm's life-cycle, e.g., firms, after becoming credit-rated, issue more debt (Faulkender and Peterson, 2006) and thus the SEO is simply an attempt to rebalance their capital structure. To account for this possibility, and in addition to controlling for leverage changes in multivariate testing, we also examine the differential market response to the issue. Abnormal returns to our two groups are independent, to a greater extent, of confounding lifecycle effects that may be present. CARs are negative for both groups on average, however, the returns to event firms are more positive for all three measures at both the mean and median and the differences are statistically significant for all six comparisons. The valuation of initiation firms suffer less at SEO issue than their unrated peers.

2. Multivariate Results

To investigate the extent to which liquidity affects SEO activity, we first investigate the likelihood of SEO issuance. If credit rating initiations improve equity market liquidity and, as Butler et al. (2005) and Lin and Wu (2013) argue, managers time SEO issues to take advantage of favorable liquidity costs, then we would expect to see a higher likelihood of SEO issuance for our initiation firms. We test this hypothesis in a limited dependent variable framework where we model the decision to issue as a function of a vector of firm characteristics and an indicator, *Event Firm*, which takes a value of one if a given observation is from our credit rating initiation subsample. The results from six model specifications examining the likelihood to issue are presented in Table 7. All specifications use probit regressions with robust standard errors clustered by Fama-French 17-industry.

[Insert Table 7 here]

The left-hand side of Table 7 imposes no restriction on the time differential from credit rating initiation to SEO issue date. The first column is a simple univariate estimation, the second adds firm characteristics and a control for the change in leverage from initiation date to SEO date (Δ*Leverage*), and the third includes year and industry fixed effects. For all three specifications, the coefficient estimates on *Event Firm* are positive and statistically significant at better than the 1% level. After becoming credit rated, firms are more likely to issue seasoned equity. The estimates are economic significance as well. The marginal effect of *Event Firm* on SEO issue, when evaluated at the means, is 24.13%, 24.10%, and 24.66% for the first three specifications, respectively.

Consistent with Faulkender and Peterson (2006), the positive and significant coefficient estimate on the change in leverage reflects managerial preference to maintain a certain capital structure. Firms whose leverage increases post-credit rating initiation are more likely to issue SEOs. The coefficient on *Leverage*, in levels, is consistent with this result. Firms with higher leverage are more likely to issue SEOs. The interpretations of the remaining variables are consistent with economic intuition. Older firms with higher sales, a greater percentage of their assets in tangible assets, and who are NYSE listed are less likely to issue reflecting their ability to better access debt markets.

To ensure that our results are not driven by outliers and that our sample does not suffer from a right-censoring bias. We reevaluate our full specification but impose a requirement that the SEO issuance occurs in one, three, and five year following the credit rating initiation date. The results of this exercise are presented in columns (4) through (6). The inferences from our full sample estimation are consistent regardless of the additional restriction. For all three specifications, estimates on *Event Firm* are positive and significant suggesting credit rating initiations are associated with an increased likelihood of SEO issuance. Economically, the marginal effect of *Event Firm* when evaluated at the mean values of the remaining covariates increases the likelihood of SEO issuance of 6.55% over one-year, 13.15% over three-years, and 16.57% over the five-years following the credit rating initiation after controlling for the heterogeneity in firm characteristics.

We then examine the time to SEO issuance using a Cox proportional hazards model to estimate a firm's duration of time until it issues seasoned equity. The direction of the relation between becoming credit rated and the time to SEO is less clear than the likelihood to issue and the valuation effects for doing so. It could be the case that firm's with enhanced equity liquidity resulting from the credit rating initiations choose to issue a SEO earlier than its less-liquid peers. However, this assumes that the firm's are unable or unwilling to access public debt markets to meet their financing needs. Faulkender and Peterson (2006) argue that credit rated firms are to increase their leverage by accessing public debt markets. If that is the case, then it is less likely that these firms would need to issue a SEO to raise capital. We test these competing hypotheses with a proportional hazards model.

The proportional hazards model is ideal in this setting as it deals with both censored observations and the non-normal distribution of the dependent variable. Our framework models *Time to SEO* as a function of *Event Firm*, our primary variable of interest, and a vector of firm characteristics. Recall, proportional hazard models seek to explain the time to failure, or action (e.g., to examine the relationship between an oil additive and the time to engine failure a researcher would use a proportional hazards model). As such a positive coefficient estimate indicates that the time to failure, SEO issuance in our case, is shorter given higher values of the covariate. The results of this testing are presented in Table 8.

[Insert Table 8 here]

Model 1 includes *Event Firm* as the only covariate. The negative and marginally significant coefficient estimate of -0.168 indicates that the time to SEO issuance is longer for credit rating initiation firms. The hazard ratio provides an intuitive interpretation of this result. Firms in the initiation subsample are 0.845 times less likely to issue on a given day given that they had not already done so. Model 2 repeats this testing controlling for firm characteristics. Again the negative and marginally significant coefficient estimate indicates that the time to issue is longer for credit rating initiation firms than for our control firms (hazard ratio of 0.848). Model 3 adds year and industry fixed effects. In this specification, the significance of the coefficient estimate on *Event Firm* subsides. There is no difference in the time to SEO for firms in the initiation subsample relative to firms in the control subsample. We interpret this result in our full model specification as evidence that credit initiation firms have increased options in their choice of financing.

Finally, we examine the abnormal returns to the issuing firms in our sample controlling for confounding effects. Market reactions are less dependent on firm lifecycle effects thus offer a cleaner setting to examine the rating's effect on liquidity. Table 9 presents the results of OLS regressions where CARs over our three time horizons are the dependent variables in three model specifications. Again, we include, as our primary variable of interest, *Event Firm* which is an indicator taking a value of one if the observation is for a credit rating initiation firm and zero otherwise. Standard errors in all specifications are clustered by year. The first three columns present the results from univariate regressions, columns (4) through (6) include the financial characteristics of the issuing firm and the change in firm leverage, and the remaining columns include year and Fama-French 17-industry controls. The results are consistent regardless of the specification used.

[Insert Table 9 here]

Coefficient estimates are positive for all nine specifications and are statistically significant at better than the 10% for all nine model specifications suggesting the credit rating firm's CARs are more positive (less negative) than the CARs for non-rated firms. The results are economically meaningful as well. In the first three columns, the CARs to our control firm subsample, the constant, are negative and statistically significant. In unreported results, we test whether the sum of the constant and the coefficient estimate on *Event Firm* is equal to zero. We cannot reject this null, the sum of the two is equal to zero, for any of the first three specifications. The positive effects of becoming credit rated and the liquidity that results mitigates the negative effects of SEO issuance for our initiation firms.

Columns (4) through (9) support the differential result even after controlling for firm, industry, and year effects. The estimates on *Event Firm* are all positive and significant. The estimates on the intercepts are still negative, but the significance drops. This is largely the result of the inclusion of Δ*Leverage* and *Prior Return*. Firms whose leverage increases post credit initiation date suffer less at SEO because the market interprets the issue as a rebalance of the firm's capital structure. *Prior Return* has the opposite effect. Firms who have seen a larger stock price rise in the past year suffer more at SEO due to the market interpreting the issue as manager's issuing when equity is overvalued.

G. Conclusion

Credit rating agencies play a crucial role is alleviating the informational asymmetries that exist in financial markets. Rating changes are predictive of changes in measures of adverse selection in equity trading patterns (Odders-White and Ready, 2006). The rating itself both reflects the asymmetric information present and serves to reduce its adverse selection costs in equity trading. In contrast to prior literature, this paper examines the effects that a credit rating initiation (becoming rated for the first time) has for the trading behavior of the firm's equity. Specifically, the extent to which the credit ratings reduces information asymmetry and improves secondary market equity liquidity.

The revisions in investor beliefs about the adverse selection costs to transacting in the firm's equity that ensue from the credit rating initiation bring about significant changes in firm's secondary market equity. Be it through the introduction of new information or the validation of prior beliefs, the credit rating initiation produces economically meaningful changes in the trading patterns of the firm's equity. Our analysis shows that measures of secondary market liquidity, i.e., *Amihud Liquidity* and trading volume, increase surrounding the credit rating initiation while measures of adverse selection costs, i.e., *Ask-Bid Spread*, fall. We then investigate the extent to which managers, seeking to maximize firm value, are able to exploit the favorable changes in secondary market liquidity.

The long-term, permanent effects of being credit rated on equity liquidity produces differential effects on SEO issuance activity. Credit rating initiation firms are 178.84% more likely to issue a SEO following the credit rating initiation than their propensity-score matched controls. Managers are more likely to issue following the initiation.

To account for the possibility that SEO activity following credit rating is simply a function of the life-cycle of the firm, we examine the abnormal equity returns to the firms in our subsamples. We show that the risk-adjusted, cumulative abnormal returns to our event firms are more positive (less negative) surrounding the SEO issue. The fact that credit rating initiation firms are more likely to issue and suffer less in terms of valuation suggest that the effects on liquidity are non-transitory. The adverse selection costs of transacting in the firm's equity fall post-rating and the price support in terms of secondary market liquidity rises.

In summary, information asymmetry and the adverse selection costs it engenders impose real economic costs for financial transactions. Credit rating agencies serve to mitigate the cost of transacting by decreasing asymmetries and fostering market liquidity. The effects of being rated reduce the costs to firms in raising external capital and thus are of primary concern to managers seeking maximize firm value.

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Table 1: Distribution of Rating Initiations

This table provides summary statistics on the distribution of new credit ratings by year, industry, and rating class. The sample consists of new long-term issuer credit rating initiations by Standard and Poor's over the time period January 1st, 1991 through December 31st, 2010. Firms are identified as having obtained a new issuer rating if their prior rating, as identified by Bloomberg Data Services, is either missing, blank, or contains a value of "NR" which identifies a firm as being not-rated. Firms are classified in to 17 industries following the classification methodology of Fama and French (1997).

Year		**Fama-French 17 Industry**		**S&P Long-Term Credit Rating**	
Year	**Frequency**	**Year**	**Frequency**	**Year**	**Frequency**
1991	24	FOOD	30	AAA	2
1992	35	MINING	18	AA+	1
1993	42	OIL	82	AA	7
1994	47	CLTHS	25	AA-	8
1995	57	DURBL	25	A+	22
1996	93	CHEM	19	A	49
1997	126	CNSUM	38	A-	53
1998	133	CNSTR	42	BBB+	61
1999	91	STEEL	28	BBB	103
2000	79	FABPR	5	BBB-	111
2001	43	MACHN	134	BB+	61
2002	54	CARS	22	BB	111
2003	51	TRANS	48	BB-	210
2004	49	UTILS	55	B+	203
2005	53	RTAIL	64	B	116
2006	46	FINAN	181	B-	42
2007	37	OTHER	366	CCC+	12
2008	25			CCC	1
2009	35			D	1
2010	62				
Total	**1182**				

Table 2: Changes in Equity Liquidity

This table presents descriptive statistics on the changes in various measures of a firm's equity liquidity surrounding the initiation of a new long-term issuer credit rating. The sample covers the time period January 1st, 1991 through December 31st, 2010. Amihud Liquidity is calculated as the reciprocal of the absolute return of a issue on a given day divided by that day's dollar volume all multiplied by 1x106 for scaling purposes (Amihud, 2002). Ln(Volume) is the natural log of the issue's daily trading volume. Ask-Bid Spread is the difference between an issue's ask and bid prices at closing. All three liquidity measures are the percentage changes in averages taken for a given time period pre- and post-rating and exclude the time period from 10 trading days before the rating to 10 trading days after. Panels A details the percentage in Amihud Liquidity, Volume, and Ask-Bid Spread. Panel B presents the results of OLS tests looking at the association between the rating obtained and the changes in liquidity measures. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Changes in Equity Liquidity

	N	Mean	Median	Std. Dev.	p5	p25	p75	p95
Amihud Liquidity Changes								
Amihud 30-day	1182	0.4369 [c]	0.0567 [c]	1.4538	-0.6675	-0.3086	0.6354	2.8122
Amihud 45-day	1182	0.4189 [c]	0.0709 [c]	1.2834	-0.6614	-0.2769	0.6029	2.4072
Amihud 60-day	1182	0.4567 [c]	0.0781 [c]	1.4657	-0.6650	-0.2600	0.6384	2.5134
Amihud 90-day	1182	0.4774 [c]	0.1223 [c]	1.4256	-0.6589	-0.2292	0.6343	2.5246
Volume Changes								
Volume 30-day	1182	0.2941 [c]	0.0557 [c]	0.9388	-0.5301	-0.2383	0.4546	2.0137
Volume 45-day	1182	0.2662 [c]	0.0684 [c]	0.8106	-0.5076	-0.2092	0.4709	1.8249
Volume 60-day	1182	0.2615 [c]	0.0743 [c]	0.7653	-0.4964	-0.1997	0.4472	1.7641
Volume 90-day	1182	0.2954 [c]	0.0842 [c]	0.8369	-0.4702	-0.1748	0.4629	1.7179
Ask-Bid Spread Changes								
Ask-Bid 30-day	1182	-0.0183 [a]	-0.0313 [c]	0.3178	-0.4909	-0.1936	0.1071	0.4599
Ask-Bid 45-day	1182	-0.0213 [b]	-0.0370 [c]	0.3190	-0.4749	-0.1892	0.1000	0.5000
Ask-Bid 60-day	1182	-0.0242 [b]	-0.0426 [c]	0.3229	-0.4591	-0.1978	0.0929	0.4838
Ask-Bid 90-day	1182	-0.0480 [c]	-0.0631 [c]	0.3275	-0.5157	-0.2172	0.0701	0.5253

Table 2: Changes in Equity Liquidity (Cont.)

Panel B: Rating Obtained and Liquidity Changes												
	Amihud Liquidity				Volume				Ask-Bid Spread			
	30-day	45-day	60-day	90-day	30-day	45-day	60-day	90-day	30-day	45-day	60-day	90-day
Rating	0.0313 [c]	0.0270 [b]	0.0388 [c]	0.0392 [c]	0.0192 [b]	0.0117 [a]	0.0136 [b]	0.0187 [c]	-0.0067 [b]	-0.0074 [c]	-0.0079 [c]	-0.0085 [c]
	(2.602)	(2.543)	(3.210)	(3.334)	(2.467)	(1.735)	(2.150)	(2.711)	(-2.431)	(-2.693)	(-2.862)	(-3.052)
Constant	0.0567	0.0910	-0.0141	0.0019	0.0615	0.1247	0.0964	0.0682	0.0633 [a]	0.0694 [b]	0.0729 [b]	0.0565
	(0.373)	(0.677)	(-0.092)	(0.013)	(0.626)	(1.469)	(1.206)	(0.781)	(1.814)	(1.983)	(2.067)	(1.587)
Observations	1182	1182	1182	1182	1182	1182	1182	1182	1182	1182	1182	1182
Adj-R^2	0.006	0.005	0.009	0.009	0.005	0.003	0.004	0.006	0.005	0.006	0.007	0.008

Table 3: Validation of Control Sample

This table reports summary statistics on the financial characteristics of event and control firms in the sample for the fiscal year end prior to the event date. Control firms are unrated firms matched based on the closest absolute-difference in their propensity score to that of an event firm following the methodology of Faulkender and Peterson (2006). Propensity scores are calculated as the output from a probit estimation using Ln(Total Assets), Ln(Sales), Ln(1+Age), Leverage, Market-to-Book, ROS, PPE/TA, R&D/Sales, Advertising/Sales, and σ(asset return) as explanatory variables. Variable definitions are provided in appendix A. Variable medians are presented in brackets. Statistical significance is provided from results testing for differences in means using t-tests and medians using Wilcoxon sign rank tests. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

		Event Firms		Control Firms		Difference	
Variable	N	Mean	Median	Mean	Median	Mean	Median
***Ln*(Total Assets)**	1182	7.069	[6.972]	7.003	[6.825]	0.0654	[0.1466]
***Ln*(Sales)**	1182	6.485	[6.544]	6.359	[6.432]	0.1262 [b]	[0.1121] [a]
***Ln*(1+Firm Age)**	1182	2.537	[2.485]	2.549	[2.485]	-0.0123	[0.0000]
Leverage	1182	0.373	[0.359]	0.380	[0.345]	-0.0070	[0.0139]
Market-to-Book	1182	1.720	[1.218]	1.435	[0.995]	0.2852 [c]	[0.2235] [c]
ROS	1182	0.095	[0.106]	0.074	[0.096]	0.0204 [b]	[0.0092] [b]
PPE/Assets	1182	0.288	[0.203]	0.327	[0.271]	-0.0390 [c]	[-0.0682] [c]
R&D/Sales	1182	0.028	[0.000]	0.022	[0.000]	0.0069 [b]	[0.0000]
Advertising/Sales	1182	0.006	[0.000]	0.006	[0.000]	0.0003	[0.0000]
σ(Equity Return)	1182	0.030	[0.027]	0.030	[0.025]	0.0002	[0.0017] [b]

Table 4: Changes in Liquidity by Group

This table presents descriptive statistics on the changes in various measures of a firm's equity liquidity surrounding the initiation of a new long-term issuer credit rating for both event and control firms. Control firms are unrated firms matched based on the closest absolute-difference in their propensity score to that of an event firm following the methodology of Faulkender and Peterson (2006). All three liquidity measures are averaged for a given time period pre- and post-rating and exclude the time period from 10 trading days before the rating to 10 trading days after. Panels A, B and C detail changes in Amihud Liquidity, Volume, and Ask-Bid Spread, respectively. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

		Event Firms		Control Firms		Difference	
	N	Mean	Median	Mean	Median	Mean	Median
Panel A: Amihud Liquidity Changes							
Amihud 30-day	1182	0.4369 [c]	0.0567 [c]	0.2633 [c]	0.0032 [c]	0.1735 [c]	0.0535 [b]
Amihud 45-day	1182	0.4189 [c]	0.0709 [c]	0.2549 [c]	0.0045 [c]	0.1640 [c]	0.0664 [c]
Amihud 60-day	1182	0.4567 [c]	0.0781 [c]	0.2399 [c]	-0.0109 [c]	0.2168 [c]	0.0890 [c]
Amihud 90-day	1182	0.4774 [c]	0.1223 [c]	0.2580 [c]	0.0072 [c]	0.2194 [c]	0.1151 [c]
Panel B: Ask-Bid Spread Changes							
Volume 30-day	1182	0.2941 [c]	0.0557 [c]	0.1862 [c]	0.0199 [c]	0.1078 [c]	0.0358 [b]
Volume 45-day	1182	0.2662 [c]	0.0684 [c]	0.1680 [c]	0.0469 [c]	0.0981 [c]	0.0214 [a]
Volume 60-day	1182	0.2615 [c]	0.0743 [c]	0.1520 [c]	0.0249 [c]	0.1095 [c]	0.0495 [c]
Volume 90-day	1182	0.2954 [c]	0.0842 [c]	0.1571 [c]	0.0302 [c]	0.1383 [c]	0.0541 [c]
Panel C: Volume Changes							
Ask-Bid 30-day	1182	-0.0183 [a]	-0.0313 [c]	0.0337 [c]	-0.0089	-0.0520 [c]	-0.0223 [c]
Ask-Bid 45-day	1182	-0.0213 [b]	-0.0370 [c]	0.0249 [b]	-0.0126	-0.0462 [c]	-0.0244 [c]
Ask-Bid 60-day	1182	-0.0242 [b]	-0.0426 [c]	0.0192 [a]	-0.0169 [b]	-0.0434 [c]	-0.0257 [b]
Ask-Bid 90-day	1182	-0.0480 [c]	-0.0631 [c]	0.0032	-0.0342 [c]	-0.0512 [c]	-0.0289 [c]

Table 5: Multivariate Tests of Liquidity Changes

This table reports the results of multivariate ordinary-least-squares testing on the changes in various measures of a firm's equity liquidity surrounding the initiation of a new long-term issuer credit rating with fixed effects for year and industry using Fama and French 17 industry classifications and robust standard errors clustered by industries. Control firms are unrated firms matched based on the closest absolute-difference in their propensity score to that of an event firm following the methodology of Faulkender and Peterson (2006). All three liquidity measures are averaged for a given time period pre- and post-rating and exclude the time period from 10 trading days before the rating to 10 trading days after. Event Firm is an indicator which takes a value of one if the observation if for a firm which obtained a credit rating and zero otherwise. Pre-Level is the average level of the dependent variable measured over the same time frame as the dependent in the period before the rating initiation. Remaining variable definitions are provided in appendix A. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 5: Multivariate Tests of Liquidity Changes (Cont.)

	Amihud Liquidity				Volume				Ask-Bid Spread			
Dependent Variable	**30-day**	**45-day**	**60-day**	**90-day**	**30-day**	**45-day**	**60-day**	**90-day**	**30-day**	**45-day**	**60-day**	**90-day**
Event Firm	0.195 [c]	0.184 [c]	0.228 [c]	0.219 [c]	0.215 [c]	0.187 [c]	0.188 [c]	0.220 [c]	-0.051 [c]	-0.044 [b]	-0.040 [b]	-0.048 [c]
	(3.670)	(3.738)	(4.580)	(5.158)	(6.478)	(5.982)	(6.424)	(6.514)	(-2.588)	(-2.314)	(-2.163)	(-2.885)
Pre-Level	-0.000 [c]	-0.001 [c]	-0.000 [c]	-0.000 [c]	-0.140 [c]	-0.120 [c]	-0.110 [c]	-0.118 [c]	-0.127 [a]	-0.121	-0.102	-0.098 [a]
	(-4.988)	(-5.339)	(-2.801)	(-3.757)	(-8.222)	(-9.302)	(-7.632)	(-7.413)	(-1.771)	(-1.595)	(-1.401)	(-1.704)
***Ln* (Total Assets)**	-0.070	-0.010	0.001	-0.016	0.035	0.044	0.052 [b]	0.039	-0.006	-0.006	0.001	-0.001
	(-1.323)	(-0.242)	(0.022)	(-0.321)	(0.998)	(1.439)	(1.993)	(1.597)	(-0.450)	(-0.451)	(0.040)	(-0.064)
***Ln* (Sales)**	0.029	0.010	-0.001	0.020	0.003	0.005	-0.003	0.013	-0.006	-0.001	-0.001	-0.006
	(0.618)	(0.272)	(-0.017)	(0.432)	(0.107)	(0.196)	(-0.144)	(0.502)	(-0.481)	(-0.088)	(-0.126)	(-0.588)
***Ln* (1+Firm Age)**	-0.038	-0.017	0.011	0.007	0.002	0.013	0.011	-0.010	0.016 [a]	0.015 [a]	0.017 [a]	0.014 [b]
	(-1.058)	(-0.633)	(0.342)	(0.225)	(0.073)	(0.470)	(0.423)	(-0.379)	(1.700)	(1.887)	(1.783)	(2.057)
Leverage	0.215	0.194	0.199	0.193	-0.017	-0.013	-0.035	-0.022	-0.002	0.005	-0.015	-0.016
	(1.231)	(1.426)	(1.111)	(1.067)	(-0.172)	(-0.152)	(-0.388)	(-0.223)	(-0.081)	(0.123)	(-0.391)	(-0.428)
Market-toBook	0.016	0.025	0.043 [b]	0.058 [c]	0.030 [b]	0.040 [c]	0.046 [c]	0.051 [c]	0.004	0.006	0.007 [a]	0.007
	(0.611)	(1.247)	(2.107)	(2.669)	(2.365)	(3.496)	(3.522)	(3.911)	(1.105)	(1.482)	(1.850)	(1.345)
ROS	0.167	0.193	0.199	0.221	0.040	-0.040	-0.043	-0.081	-0.016	-0.044	-0.032	-0.004
	(1.027)	(1.322)	(1.143)	(1.154)	(0.459)	(-0.506)	(-0.477)	(-0.898)	(-0.339)	(-0.999)	(-0.694)	(-0.078)
PPE/Assets	-0.074	-0.167	-0.136	-0.207	-0.195 [a]	-0.197 [b]	-0.196 [a]	-0.243 [b]	0.028	0.018	0.042	0.043
	(-0.447)	(-1.131)	(-0.796)	(-1.185)	(-1.957)	(-2.042)	(-1.925)	(-2.345)	(0.663)	(0.416)	(1.034)	(1.090)
R&D/Sales	-0.202	-0.448	-0.744 [a]	-0.778 [b]	0.077	0.021	0.009	0.072	-0.102	-0.154 [a]	-0.165	-0.201
	(-0.457)	(-1.338)	(-1.887)	(-2.071)	(0.334)	(0.084)	(0.032)	(0.265)	(-1.162)	(-1.703)	(-1.280)	(-1.339)
Advertising/Sales	1.062	1.215	0.569	1.433	1.542	1.149	1.032	2.401 [a]	0.546	0.275	0.137	0.154
	(0.348)	(0.443)	(0.194)	(0.538)	(0.891)	(0.768)	(0.762)	(1.670)	(0.732)	(0.445)	(0.240)	(0.267)
σ(Equity Return)	3.021	2.673	5.330	6.133	5.641 [c]	3.469 [c]	3.088 [b]	1.903 [a]	-1.232	-1.721 [b]	-1.559 [b]	-1.991 [c]
	(1.127)	(0.929)	(1.282)	(1.528)	(3.443)	(2.580)	(2.146)	(1.666)	(-1.518)	(-2.549)	(-2.309)	(-2.903)
NYSE	0.030	-0.018	-0.021	0.002	0.066	0.066	0.072 [a]	0.060 [a]	0.042 [b]	0.043 [b]	0.037 [b]	0.037 [b]
	(0.345)	(-0.236)	(-0.244)	(0.028)	(1.567)	(1.607)	(1.826)	(1.658)	(2.040)	(2.378)	(2.284)	(2.280)
Constant	0.536 [a]	0.362 [a]	0.075	0.100	1.243 [c]	0.973 [c]	0.848 [c]	1.025 [c]	0.144 [a]	0.114	0.027	0.066
	(1.797)	(1.725)	(0.240)	(0.309)	(5.529)	(4.840)	(4.133)	(4.275)	(1.780)	(1.560)	(0.329)	(0.748)
Observations	2364	2364	2364	2364	2364	2364	2364	2364	2364	2364	2364	2364
Adj. R^2	0.058	0.067	0.072	0.093	0.087	0.083	0.079	0.088	0.043	0.050	0.055	0.084

Table 6: Seasoned Equity Offerings

This table presents descriptive statistics on seasoned equity offerings for event and control firms following the initiation of a new long-term issuer credit rating. The sample covers the time period January 1st, 1991 through December 31st, 2010. SEO Flag is an indicator which takes a value of one if the firm issues a seasoned equity offer following the new rating and zero otherwise. Time to SEO is the natural log of the issue's daily trading volume. Abnormal returns surrounding the issue are calculated using the Carhart (1997) four-factor model estimated over the period 282 to 30 days prior to issue date and then summed for various horizons surrounding the issue date. Panels A and B provide summary statistics for the full sample and by group, respectively. t-tests for differences in means and Wilcoxon sign rank tests are performed on the mean and median values for each measure as well as for differences in group results. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

	N	Mean	Median	Std. Dev.	p5	p25	p75	p95
Panel A: Full Sample								
SEO Flag	2364	0.2538	0.0	0.4353	0.0	0.0	1.0	1.0
Time to SEO	580	1204.98	630.5	1385.39	19.5	210.5	1702.5	4287.5
Issue Size	580	0.3296	0.1843	0.4763	0.0631	0.1080	0.3389	1.1406
CAR[-3,3]	580	-0.0162 [c]	-0.0180 [c]	0.0773	-0.1455	-0.0627	0.0308	0.1008
CAR[-5,5]	580	-0.0136 [c]	-0.0172 [c]	0.0930	-0.1776	-0.0675	0.0438	0.1345
CAR[-10,10]	580	-0.0015	-0.0104	0.1139	-0.1902	-0.0703	0.0641	0.1797

Panel B: Comparison by Groups

	Event Firms			Control Firms			Difference	
	N	Mean	Median	N	Mean	Median	Mean	Median
SEO Flag	1182	0.3689	-	1182	0.1323	-	0.2366 [c]	-
Time to SEO	432	1259.28	697.00	148	1046.51	473.50	212.77	223.50 [a]
Issue Size	432	0.3234	0.1774	148	0.3477	0.2094	-0.0243	-0.0320 [b]
CAR[-3,3]	432	-0.0108 [c]	-0.0149 [c]	148	-0.0326 [c]	-0.0264 [c]	0.0218 [c]	0.0115 [b]
CAR[-5,5]	432	-0.0071	-0.0156 [b]	148	-0.0328 [c]	-0.0243 [c]	0.0257 [c]	0.0087 [b]
CAR[-10,10]	432	0.0066	-0.0067	148	-0.0257 [c]	-0.0224 [c]	0.0322 [c]	0.0157 [b]

Table 7: Propensity to Issue

This tables reports the results from probit analyses where the likelihood that a firm issues a seasoned equity offering (SEO) following a credit rating initiation is modeled as a function of the financial characteristics of the firm and an indicator, Event Firm, which takes a value of one if the observation is for an event firm and zero otherwise. Control firms are unrated firms matched based on the closest absolute-difference in their propensity score to that of an event firm following the methodology of Faulkender and Peterson (2006). All three liquidity measures are averaged for a given time period pre- and post-rating and exclude the time period from 10 trading days before the rating to 10 trading days after. Variable definitions are provided in appendix A. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 7: Propensity to Issue (Cont.)

	Dependent Variable = SEO Issue (1 if yes)					
	Full Sample Horizon			One-Year	Three-Year	Five-Year
	(1)	(2)	(3)	(4)	(5)	(6)
Event Firm	0.781 [c]	0.817 [c]	0.861 [c]	0.552 [c]	0.643 [c]	0.707 [c]
	(5.658)	(10.661)	(10.643)	(5.995)	(5.379)	(6.719)
ΔLeverage		3.113 [c]	3.182 [c]	-0.372	1.368 [c]	2.590 [c]
		(6.230)	(6.794)	(-0.970)	(2.886)	(5.199)
Prior Return		0.026	0.034	0.109 [c]	0.052	0.023
		(1.160)	(1.445)	(3.040)	(1.474)	(0.662)
σ(Equity Return)		-3.471 [a]	-5.083 [b]	-4.005	-3.750	-3.627
		(-1.903)	(-2.292)	(-1.060)	(-1.454)	(-1.372)
***Ln*(Total Assets)**		0.109 [b]	0.000	0.030	-0.034	-0.044
		(2.546)	(0.001)	(0.304)	(-0.539)	(-0.622)
***Ln*(Sales)**		-0.251 [c]	-0.172 [c]	-0.199 [c]	-0.144 [c]	-0.138 [b]
		(-4.744)	(-2.924)	(-2.954)	(-2.984)	(-2.470)
***Ln*(1+Firm Age)**		-0.085	-0.114 [c]	-0.261 [c]	-0.184 [c]	-0.197 [c]
		(-1.503)	(-2.631)	(-4.838)	(-4.592)	(-4.224)
Leverage		0.643 [c]	0.753 [c]	0.178	0.515 [c]	0.463 [c]
		(8.151)	(6.802)	(1.209)	(2.722)	(4.069)
Market-to-Book		-0.005	0.016	0.034	0.020	0.012
		(-0.250)	(0.749)	(1.309)	(0.681)	(0.612)
ROS		0.169	-0.038	-0.153	0.020	0.026
		(1.216)	(-0.205)	(-0.931)	(0.099)	(0.103)
PPE/Assets		-0.082	-0.212	-0.276 [a]	-0.456 [b]	-0.425 [a]
		(-0.399)	(-1.023)	(-1.737)	(-2.296)	(-1.904)
R&D/Sales		-0.087	0.236	-0.791	-0.586	-0.034
		(-0.375)	(0.799)	(-0.929)	(-1.000)	(-0.049)
Advertising/Sales		-9.193 [c]	-6.175 [c]	-10.422 [c]	-3.825	-4.746 [b]
		(-5.451)	(-4.396)	(-6.274)	(-1.552)	(-2.149)
NYSE		0.575 [c]	0.493 [c]	0.452 [c]	0.408 [c]	0.427 [c]
		(7.695)	(5.839)	(3.830)	(4.258)	(3.473)
Constant		-0.603 [b]	-0.133	-0.757 [b]	-0.067	0.047
		(-2.302)	(-0.393)	(-2.048)	(-0.148)	(0.101)
Year Controls	N	N	Y	Y	Y	Y
Industry Controls	N	N	Y	Y	Y	Y
Observations	2364	2364	2364	2364	2364	2364
Pseudo R^2	0.0676	0.186	0.217	0.149	0.148	0.176

Table 8: Credit Ratings and Time to Seasoned Equity Offering

We employ a Cox proportional hazard model to estimate the effect of a credit rating initiation on the decision to issue a seasoned equity offering (SEO). Specifically, we model the duration of time until a firm issues a SEO offering against a set of control variables and an indicator, Event Firm, which takes a value of one if the observation is for an event firm and zero otherwise. Positive coefficients imply that a given firm is more likely to issue a SEO given an increase in the independent variable. We restrict our SEO sample to only those SEOs which occur within 5-years following the credit rating event. Control firms are unrated firms matched based on the closest absolute-difference in their propensity score to that of an event firm following the methodology of Faulkender and Peterson (2006). Variable definitions are provided in appendix A. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Model 1		Model 2		Model 3	
	Coefficient	**Hazard Ratio**	**Coefficient**	**Hazard Ratio**	**Coefficient**	**Hazard Ratio**
Event Firm	-0.168 [b]	0.845 [b]	-0.164 [a]	0.848 [a]	-0.144	0.866
	(-1.996)		(-1.681)		(-1.275)	
ΔLeverage			-0.084	0.919	-0.211	0.809
			(-0.398)		(-0.822)	
Prior Return			0.032 [b]	1.033 [b]	0.045 [c]	1.046 [c]
			(2.104)		(2.800)	
σ(Equity Return)			4.223	68.220	-0.169	0.844
			(1.003)		(-0.042)	
Ln(Total Assets)			0.011	1.011	-0.052	0.949
			(0.195)		(-0.684)	
Ln(Sales)			0.028	1.028	0.016	1.017
			(0.715)		(0.247)	
Ln(1+Firm Age)			-0.089	0.915	-0.178 [b]	0.837 [b]
			(-1.384)		(-2.554)	
Leverage			-0.366 [b]	0.693 [b]	-0.256	0.774
			(-2.355)		(-1.334)	
Market-to-Book			0.034 [a]	1.034 [a]	-0.001	0.999
			(1.657)		(-0.052)	
ROS			-0.178	0.837	-0.115	0.891
			(-0.913)		(-0.507)	
PPE/Assets			-0.430 [b]	0.650 [b]	-0.671 [b]	0.511 [b]
			(-2.511)		(-2.391)	
R&D/Sales			-0.447	0.640	-0.556	0.573
			(-0.796)		(-0.696)	
Advertising/Sales			-5.914	0.003	-4.843	0.008
			(-1.095)		(-0.822)	
NYSE			-0.097	0.908	0.119	1.127
			(-0.852)		(0.846)	
Year Controls	N		N		Y	
Industry Controls	N		N		Y	
Observations	580		580		580	
Wald Chi^2	3.985 [b]		446.9 [c]		373.0 [c]	

Table 9: Abnormal Returns and Seasoned Equity Offerings

This table reports the results of multivariate ordinary-least-squares testing on the abnormal returns to firms at the issuance of a seasoned equity offering (SEO). Cumulative abnormal returns are calculated using the Carhart (1997) four-factor model estimated over the period 282 to 30 days prior to announcement prior to issue date and then summed for various horizons surrounding the issue date. Control firms are unrated firms matched based on the closest absolute-difference in their propensity score to that of an event firm following the methodology of Faulkender and Peterson (2006). Event Firm is an indicator which takes a value of one if the observation if for a firm which obtained a credit rating preceding the SEO offering and zero otherwise. Remaining variable definitions are provided in appendix A. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

Dependent Variable	**CAR[-3,3]**	**CAR[-5,5]**	**CAR[-10,10]**	**CAR[-3,3]**	**CAR[-5,5]**	**CAR[-10,10]**	**CAR[-3,3]**	**CAR[-5,5]**	**CAR[-10,10]**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Event Firm	0.0218 [b]	0.0257 [b]	0.0322 [b]	0.0183 [a]	0.0252 [b]	0.0264 [a]	0.0206 [b]	0.0256 [b]	0.0263 [a]
	(2.443)	(2.240)	(2.397)	(1.937)	(2.098)	(1.802)	(2.134)	(2.055)	(1.748)
SEO Issue Size				0.0006	0.0063	0.0197	-0.0020	0.0042	0.0138
				(0.068)	(0.584)	(1.231)	(-0.221)	(0.344)	(0.860)
ΔLeverage				0.0533 [b]	0.0199	0.0512 [a]	0.0532 [b]	0.0170	0.0477 [a]
				(2.232)	(0.752)	(1.792)	(2.295)	(0.622)	(1.737)
Prior Return				-0.0032 [b]	-0.0061 [c]	-0.0086 [c]	-0.0032 [b]	-0.0060 [c]	-0.0079 [c]
				(-2.545)	(-3.934)	(-4.431)	(-2.386)	(-3.887)	(-3.481)
σ(Equity Return)				-0.0696	0.0873	0.6243 [a]	-0.1183	0.0693	0.5944
				(-0.239)	(0.236)	(1.707)	(-0.404)	(0.176)	(1.527)
Ln(Total Assets)				0.0051	0.0080	0.0126 [b]	0.0053	0.0113 [a]	0.0175 [c]
				(1.216)	(1.427)	(2.390)	(1.138)	(1.690)	(2.700)
Ln(Sales)				-0.0021	-0.0046	-0.0089 [b]	-0.0028	-0.0083	-0.0142 [b]
				(-0.559)	(-1.085)	(-2.234)	(-0.617)	(-1.306)	(-2.429)
Ln(1+Firm Age)				-0.0020	-0.0036	-0.0074	0.0018	-0.0009	-0.0039
				(-0.397)	(-0.620)	(-0.950)	(0.315)	(-0.136)	(-0.467)
Leverage				-0.0179	-0.0392 [b]	-0.0662 [b]	-0.0179	-0.0422 [b]	-0.0679 [b]
				(-1.336)	(-2.127)	(-2.086)	(-1.512)	(-2.449)	(-2.319)
Market-to-Book				-0.0008	-0.0021	0.0034	-0.0016	-0.0027	0.0029
				(-0.264)	(-0.638)	(0.941)	(-0.534)	(-0.878)	(0.781)
ROS				0.0111	0.0100	-0.0132	0.0096	0.0137	-0.0096
				(0.761)	(0.475)	(-0.494)	(0.653)	(0.723)	(-0.371)
PPE/Assets				0.0017	-0.0079	-0.0053	0.0300 [a]	0.0153	0.0107
				(0.144)	(-0.533)	(-0.263)	(1.855)	(0.665)	(0.384)
R&D/Sales				-0.0383	-0.0215	-0.0867	-0.0298	-0.0365	-0.1466
				(-0.597)	(-0.300)	(-1.163)	(-0.395)	(-0.418)	(-1.604)
Advertising/Sales				-0.0452	-0.0330	-0.0298	-0.2968	-0.3314	-0.3382
				(-0.144)	(-0.091)	(-0.050)	(-0.827)	(-0.792)	(-0.547)
NYSE				-0.0083	-0.0132	-0.0074	-0.0059	-0.0101	-0.0040
				(-0.652)	(-1.034)	(-0.546)	(-0.456)	(-0.768)	(-0.288)
Constant	-0.0326 [c]	-0.0328 [c]	-0.0257 [c]	-0.0332	-0.0226	-0.0265	-0.0395	0.0023	-0.0043
	(-4.969)	(-3.915)	(-2.944)	(-0.995)	(-0.631)	(-0.705)	(-0.909)	(0.045)	(-0.096)
Year Controls	N	N	N	N	N	N	Y	Y	Y
Industry Controls	N	N	N	N	N	N	Y	Y	Y
Observations	580	580	580	580	580	580	580	580	580
Adj. R^2	0.015	0.014	0.015	0.042	0.044	0.065	0.097	0.086	0.109

Appendix A: Variable Definitions

Variable	Definition
Amihud Liquidity	Calculated as the reciprocal of the absolute value of the firm's daily return scaled by the firm's daily dollar volume and then averaged for a given period before and after the event window. This variable is multiplied by $1\text{x}10^7$ for scaling purposes.
Volume	The daily trading volume as reported by *CRSP*.
Ask-Bid Spread	The difference between the end of day ask and bid price as reported by *CRSP*.
Rating	A numerical representation of the *S&P* rating received by the rated firm. Higher numbers represent increased credit worthiness.
***Ln*(Total Assets)**	The natural log of book total assets in the fiscal year end immediately preceding the initiation of a credit rating.
***Ln*(1+Firm Age)**	The natural log of one plus the number of years a firm has existed in *Compustat*.
***Ln*(Sales)**	The natural log of total revenue in the fiscal year end immediately preceding the initiation of a credit rating.
Leverage	Total long-term debt plus the current portion of long-term debt divided by total equity in the fiscal year end immediately preceding the initiation of a credit rating.
ΔLeverage	The difference in firm leverage from the quarter-ending immediately preceding the SEO date less the leverage from the quarter-ending immediately preceding the initiation date.
Market-to-Book	Market value of common shares outstanding to book value of shares in the fiscal year end immediately preceding the initiation of a credit rating.
ROS	EBIT divided by total revenue in the fiscal year end immediately preceding the initiation of a credit rating.
PPE/Assets	Net property, plant, and equipment scaled by book total assets in the fiscal year end immediately preceding the initiation of a credit rating.
R&D/Sales	R&D expenses scaled by total revenue in the fiscal year end preceding the initiation of a credit rating.
Advertising/Sales	Advertising expenses scaled by total revenue in the fiscal year end preceding the initiation of a credit rating.
Tax Rate	Effective firm tax rate is calculated as reported tax expense scaled by EBIT in the fiscal year end preceding the initiation of a credit rating.
σ(Equity Return)	The standard deviation of firm's daily returns over a 252 trading-day period starting 282 days before the event and ending 30 days before the event.
SEO Flag	An indicator variable which takes a value of one if the firm issues a seasoned equity offering and zero otherwise.
Time to SEO	The time in days from a credit rating initiation to the issue date of a seasoned equity offering.
SEO Issue Size	Seasoned equity offering proceeds scaled by the market capitalization of the issue firm evaluated at the credit rating initiation.
NYSE	An indicator which takes a value of one if the firm's equity trades on the NYSE and zero otherwise.
CAR	The cumulative abnormal return surrounding the SEO issue. Daily abnormal equity returns in the issue windows are computed using a Carhart (1997) four-factor model estimated over the period 282 to 30 days prior to issue date.

Appendix B: Probit Estimation

Table reports the results of the probit model used to calculate propensity scores. We then use these scores to uniquely match our credit rating initiation firms to the respective control firm. Variable definitions are provided in appendix A. The model includes year fixed effects. [a], [b], and [c] indicate statistical significance at the 10%, 5%, and 1%, respectively.

	Limited Dependent
	Rated = 1
***Ln*(Total Assets)**	0.6750 [c]
	(154.60)
***Ln*(1+Age)**	0.3943 [c]
	(47.69)
Leverage	1.6635 [c]
	(61.47)
Market-to-Book	0.0063
	(1.40)
ROS	-0.3627 [c]
	(-10.93)
PPE/Assets	0.1030 [c]
	(4.50)
R&D/Sales	-1.0720 [c]
	(-11.84)
Advertising/Sales	2.0997 [c]
	(5.16)
Tax Rate	-0.0029
	(-0.11)
Intercept	-6.5564 [c]
	(-130.49)
Observations	121,134
Pseudo-R^2	0.523

IV. Essay 3: Social Clustering, Informal Contracting, and Firm Governance[30]

Garrett A. McBrayer

A. Abstract

Using an extensive database that covers the social networks of business executives, we identify "social clustering" of CEOs and directors of S&P 1500 firms, roughly defined as close knit communities within a network, and study its effects on corporate governance and firm value. Prior literature has shown that network clustering improves information transmission and strengthens informal contracting, but may also induce excessive loyalty, homogenization of ideas, or propagate the effects of shocks throughout the network. We find that the degree to which a CEO and her directors overlap in social communities affects the governance of the firm and that these effects are conditional upon the potential for adverse reputation costs faced by the members of the board. For firms whose boards face relatively lower potential adverse reputation costs to bad behavior, clustering is associated with poorer governance and managerial self-dealing. For firms whose boards face relatively higher potential adverse reputation costs to bad behavior, clustering acts as an implicit enforcement mechanism complementary to explicit firm governance.

B. Introduction

With the availability of data on the social networks of business professionals from data companies such as BoardEx, the study of social networks in finance is now able to examine the

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effects of social connections in the context of financial decision making. Although the study of social networks in finance is still relatively nascent, there is already evidence emerging of the importance of social networks in both investment and corporate finance settings. Roughly, there are two strands of research emerging which reach very different conclusions of the effects of social networks. The first is that social networks lead to lesser accountability, increased entrenchment, poorer decision making, reduced firm governance, and, consequently, reduced shareholder protections and lower firm value. These conclusions highlight the increased agency costs and entrenchment effects of networks. For example, Hwang and Kim (2009) and Nguyen (2011) find that monitoring weakens when CEOs and directors have social connections. Social connections between the board and the CEO compromise otherwise independent directors, resulting in higher CEO compensation and reduced pay-performance and turnover-performance sensitivity relative to less socially-connected boards. Chidambaran, Kedia, Prabhala (2012) find higher likelihood of committing fraud when a CEO forms social connections with her directors outside their professional career.

The second line of research focuses on the beneficial aspects of social connections. This research focuses largely on the improvements in information flows between connected parties and the ability of networks to act as a mechanism for implicit contracting. The former acts to reduce information asymmetries between participants while the latter supplements more formal contractual and governance mechanisms.[31] Given that our study is primarily concerned with the implicit contracting effects of social networks, we focus on the latter. Lippert and Spagnolo

[31] Larcker, So, and Wang (2013) study the relation of the centrality of the board to both accounting performance and market returns. Their paper shows that firms with central boards earn superior risk-adjusted stock returns and experience higher future growth in return-on-assets. They attribute their findings to the influence, improved information flows, and conduit of support provided by the networks of board members.

(2011) develop a model with complex and incomplete contracting wherein network dynamics offer informal information channels and provide multilateral enforcement mechanisms. Through this framework, they argue that networks may be detrimental to welfare maximization, but, that networks offer mechanisms for reducing information asymmetries and improving governance. Central to our study, they show that direct connections do not necessarily matter most as the network structure itself may act to improve the flow of private information and induce reputation effects to enforce good behavior and punish deviance. Brass and Labianca (2006) construct the mechanisms by which negative relationships in a workplace setting can affect one's financial livelihood and emotional well-being thus affecting the productive functioning of the organization as a whole. Essentially, their argument hinges on detrimental reputational effects of negative relationships that lead to ostracization by the group. In an empirical setting, Poppo and Zenger (2002) examine data on the contracts of information service providers of firms to examine the association between formal and implicit contracting. They document the interdependence of implicit contracting, or relational governance, and formal contracting. The authors conclude that informal contracting acts as a necessary complement to formal contracting.

In sum, there is increasing evidence suggesting that the structure of the network itself affects the outcomes of the network participants. What is unclear, however, is our understanding about the circumstances under which the network will induce positive effects and when the network will induce negative effects. In certain instances, the network can act to the detriment of stakeholders, e.g., by imposing principal-agent costs stemming from entrenchment on the shareholders of a firm. While, at other times, the network can act as a means of implicit contracting or relational governance in which bad behavior is punished, i.e., the potential for negative relational consequences force participants to act in accordance with the norms of the network. One limitation of the current literature, however, is that prior studies have examined the existence of a bilateral link or of individuals (groups of individuals) relative position within a network (i.e., centrality), but not the network itself. Many of these studies seek to examine the links or positions of individuals in the network alone in isolation, thus extending to the network structure us not essential. However, in other situations, it is essential to understand the dynamics of the network itself. For instance, some networks may be sparse, while others more closely knit. The differences in the dynamics between the two, may affect the way in which the network, or its participants, act. In this study, we focus on the structure of the network itself and ask the question, "Does the structure of the network affect network outcomes?" More specifically, we identify network clusters, groups of people that are densely connected with each other but relatively sparsely connected with individuals belonging to different communities, and study how these clusters affect network outcomes. For example, a CEO and her directors belonging to the same, very tightly knit communities may derive a set of benefits and costs different from simply having established a bilateral connection in the past, or by being centrally located in the network.

In this paper, we develop a measure of the interconnectedness of the network itself. Specifically, we measure and examine the effects of director clustering in the social networks of business professionals. We hypothesize that a higher fraction of the board sharing the same social cluster impacts the corporate governance of the firm by affecting the implicit contracting between the members of the cluster and thus, the firm. More specifically in environments where the potential for external, negative reputational effects are high, the cluster acts, through implicit contracting, to enforce good behavior and punish bad. However, in environments where the potential for external, negative reputational effects are low, the cluster acts as an entrenchment mechanism leading to weaker director governance and thus increased managerial self-dealing and higher agency costs consistent with traditional agency theory.

Using data from BoardEx, a company that specializes in collecting bibliographic data from annual reports and proxy statements, we construct yearly networks that comprise over 380,000 business professionals and approximately 12 million pairs of unique connections. We then apply a modularity optimization algorithm (Blondel, Guillaume, Lambiotte, and Lefebvre, 2008) to detect clusters of individuals within the data.

[Insert Figure 1 about here]

Figure 1 demonstrates a simplified example of social network clustering. Individuals inside the cluster form overlapping relationships to one another, and sparse connections to those outside of the cluster.

We identify the clusters to which the board members of Standard and Poor's 1500 firms (S&P 1500) belong. A firm level clustering variable is then constructed to measure the percentage of directors who belong to the same social cluster as the CEO. Our results suggest that clustering at S&P 1500 firms acts as an informal contracting mechanism affecting the governance of a firm. Specifically, we show that CEO-Director clustering has differential effects on the governance of the firm depending on the network environment in which the CEO-Directors are located. In environments where the potential for external reputation costs are high (low), the effects of clustering on firm governance are positive (negative). When we examine the relation between clustering and measures of corporate governance, we observe higher managerial control and entrenchment in firms who are highly clustered and whose boards face relatively lower adverse reputation effects, but lower managerial control and better shareholder protections in firms who are highly clustered with relatively higher potential adverse reputation effects. We conclude that clustering has differential effects conditional upon the potential for adverse reputation effects.

This paper makes several important contributions. First, our results add to the literature on pairwise, or bilateral, connections (for example, Hwang and Kim, 2009, and Fracassi and Tate, 2012, among others) by suggesting that the bilateral connection alone does not capture the entirety of the social relationships within a network. The existence of a pairwise connection may simply indicate the presence of a relationship, either in the past or at present, but the strength of the relationship is unknown. On the other hand, belonging to the same cluster is more descriptive of the strength of the relationship, i.e., each cluster represents a social community in which one's relationship to others within the cluster is much stronger than that toward anyone outside the cluster. Relationship within these tight-knit local neighborhoods imposes stronger informal, or implicit, contracts among members within the cluster. However, the benefits of stronger informal contracts are not without their costs. For example, network clustering may lead to the homogenization of ideas, leading to a scarcity of outside information, ideas, resources, and creativity (Janis, 1976). In the context of a firm, this may exacerbate directors' excess loyalty and obedient to the CEO's authority (Milgram, 1974; Fogel, Ma, Morck, 2012), stifle innovation, and worsen managerial entrenchment.

Second, we extend the existing literature on network clustering to business executive social networks. Having identified social clustering within the network using the methodology in Blondel et al. (2008), we construct several new measures of CEO-Director clustering to assess the degree to which board members belong to the same social network cluster as their respective CEOs. Our measures differ from measures previously documented in that they capture the structure of the network as opposed to the "connectedness" of individual within the network. The distinction allows us to evaluate the impacts of the network itself.

We also contribute to the extant literature which examines the effects of network influences on firm outcomes. Collectively, Hwang and Kim (2009), Nguyen (2011), Chidambaran et al. (2012), and El-Khatib, Fogel, and Jandik (forthcoming) find that the shareholder protections are a decreasing function of the connectedness of the CEO. We complement this literature by examining how the interconnectedness of the board with their CEO affects firm outcomes. We show that the degree to which a CEO and her directors overlap in social communities affects the governance of the firm and that these effects are conditional upon the potential for adverse reputation costs faced by the members of the board. For firms whose boards face relatively lower potential adverse reputation costs to bad behavior, clustering is associated with poorer governance and greater managerial self-dealing. For firms whose boards face relatively higher potential adverse reputation costs to bad behavior, clustering acts as an implicit enforcement mechanism complementary to explicit firm governance.

The rest of the paper is organized as follows. Section 2 provides a detailed literature review which builds our hypotheses on the relation between clustering, informal contracting, and firm governance. Section 3 describes the social connection data and the modularity optimization algorithm we use to detect whether a CEO and her directors belong to the same social cluster. Empirical results on the relation of clustering corporate governance are provided in section 4. Section 5 concludes and discusses possible extensions of this research, to further examine the financial impact of the size and density of the social communities CEO or director belongs, in order to deepen our understanding of how executive social network characteristics affect financial decision making and firm value.

C. Concept Development and Related Literature

Financial economists have ventured into social network analysis with great success finding new insights on the behavior and predictability of corporate policies and investment performance. For example, Cohen, Malloy, Frazzini (2010) document superior performance for sell-side equity analysts when they share an educational connection to senior officers of firms from their alma mater. Fracassi (2012) shows that increases in the social connections among key executive and directors of two companies lead to higher synchronicity between the levels of investments of two companies.

The depth of this literature extends beyond simply counting connections. Further examination of the social networks reveals properties beyond bilateral connections between individuals. The first is "homophily", or in its more common idiom, "birds of a feather flock together", whereby people with similar interests, personalities, upbringings, etc. are more likely to form relationships than those who do not share similar attributes (Lazarsfeld and Merton, 1954). The next is "transitivity", whereby a friend's friend is also a friend. In other words, two individuals who each have a tie to a third person are more likely to be connected, compared to individuals who do not (White, Boorman, and Breiger, 1976). The transitive and homophilic properties of social connections contribute to the natural tendency to form "clusters" of relationships within the network, resulting in local neighborhoods, communities or sub-networks that include a collection of more densely connected individuals. These clusters, varying in size and composition, augment the benefits and costs of social relationships. Members in social clusters enjoy close proximity to each other, share common friends, and may, over time, conform to similar economic and social behaviors.[32]

[32] See, for example, Irving Janis' seminal work on "groupthink."

A significant body of emerging literature examines the connections between the CEO and the board of directors of a firm. Although the scope of this literature is broad (e.g., ranging from studies on compensation, to mergers and acquisitions, to financial contracting), essentially, these studies are similar in that they all examine, at least to some degree, how the fiduciary responsibilities and incentives of the CEO and the board are affected by social or professional connections between the two. Depending on the specific question being asked, connections between a CEO and the board seem to affect the workings of a firm; sometimes to the shareholders' benefit and sometimes to their detriment.[33]

Our study builds upon prior literature that examines director independence, CEO-director social connections, and the effects of independence or connections on corporate governance and firm value. In the next section, we discuss the findings and limitations of prior studies using bilateral connections. A richer understanding of the architecture of the social network, particularly in terms of social clustering, is necessary to reveal a more nuanced picture of the inner workings of the board room, the innovation activities of a firm, the information environment in which a firm operates, and the board's effectiveness.

1. Reputation Effects

In a framework where individuals are rational and seek to optimize their respective utility functions, seeking to maximize one's personal or professional interests is a default condition. Individuals seek to maximize their personal welfare subject to a variety of budget constraints. In a corporate framework, this is what leads to the agency problems firm formalized by Jensen and Meckling (1976). Jensen and Meckling model the separation of ownership and control and develop, as a rational outcome of the subsequent optimization process, three costs to separation:

[33] See, for example, Hwang and Kim (2009), Nguyen (2011), Chidambaran et al. (2012), and El-Khatib, Fogel, and Jandik (forthcoming).

1) monitoring costs to the principal, 2) bonding expenditures of the agent, and, 3) residual loss. They show that managers rationally expropriate non-pecuniary benefits from the firm as a result of the fact that they, themselves, do not incur the full costs of doing so. Since the innovation of Jensen and Meckling, a significant body of literature has been developed which seeks to identify factors which mitigate this misappropriation. One subset of this literature examines how the reputation effects (career concerns) of CEOs and board members affect this suboptimal outcome.

Managers seek to optimize their individual welfare conditional upon the budget constraints they face. One such constraint is the potential for adverse reputation effects that arise as a result of their behavior. Kreps and Wilson (1982) develop a model by which the effects of reputation in the presence of imperfect, or asymmetric, gives rise to a “reputation effect” in repeated games. They show that “small” amounts of informational uncertainty can lead to considerable reputation concerns in finite games. Gibbons and Murphy (1992) model CEO reputation (career) concerns in an optimal compensation setting and show that reputational concerns play a significant role in optimal contracting, i.e., explicit incentives from an optimal compensation structure should be stronger for CEOs closer to retirement than for CEOs further from retirement. Their result is naturally intuitive in that reputational concerns are diminishing with the time left for adverse actions to become costly to the individual. Milbourn (2003) supports this result by showing that optimal CEO contracting is a direct function of the reputation of the CEO. Milbourn uses various measures of CEO reputation and shows a positive and economically meaningful relationship between performance-pay sensitivities and CEO reputation. Collectively, prior literature seems to suggest that reputational considerations are of concern to welfare maximization of CEOs. What about members of the board?

The literature on reputational considerations, or career considerations, of the members of a firm's board is much more scarce. This result is a logical outcome for at least two reasons: firstly, it is difficult to measure the career considerations of a given individual, much less aggregate to a group of individuals. Secondly, the function of the board is to protect the shareholders. In the event that underperformance or managerial self-dealing, it is often not the case that boards are replacement en mass. Given these reasons, the reputational concerns of board members is often overlooked in finance literature. The fact that a significant body of prior research does not exist on the reputational concerns of board members does not mean that reputational considerations are not of concern to board members. Zajac and Westphal (1996), for example, examine the selection process of members to corporate boards. They find that board members are selected based, in part, on the reputations they have developed in prior appointments. Fich and Shivdasani (2006) support this result. The authors investigate the impact of financial fraud on director appointments and show that: 1) directors who are associated with fraud experience a reduction in board seats held; 2) interlocked firms that share a director with the fraudulent firm experience a valuation decline; and, 3) the likelihood of a fraudulent director losing his directorship increases with stronger firm governance. It follows, since board appointments are a function of the reputation of the individual director, that directors who are better connected, i.e., more current or previous board appointments, face greater potential reputation costs to adverse actions, ceteris paribus. The outcome on firm governance is then that better connected boards, who face greater reputation costs, would have greater incentive to align the objectives of the firm with the shareholders interest. However, since the process of developing a reputation and board selections are endogenous to each other (i.e., more board appointments gives a better opportunity to develop a better reputation which leads to more board appointments), this is only part of the story. Consider, for example, an individual with a relatively less-developed reputation. For this individual, the opportunity to increase their board appointments, and the career concerns that result, are significant pressures to act in accordance with shareholder interests. Together these conjectures lead to the following null hypothesis:

H1: The potential for adverse reputation costs to the reputations of directors on a firm's board are positively related to the governance of the firm.

2. Informal Contracting

Informal contracts arise when the marginal costs of formal contracting exceed the marginal benefits. In these cases, informal contracts serve to outline the behaviors/actions of the contractees in order to achieve some pre-defined outcome. Roughly defined, informal contracts are non-contractual, relationship-based agreements between parties (Azariadas and Stiglitz, 1983; Azariadis, 1975; Baily, 1974; among others). For example, Boot, Greenbaum, and Thakor (1993) develop a model that explains the use of legally unenforceable, discretionary contracts in circumstances where legally enforceable contracting is possible. The authors explain this seemingly paradoxical result by arguing that considerations of trust and reputation capital are sufficient to enforce the components of the informal contract. The better the reputation of a contracting party, the greater the flexibility permitted in contracting. If a trusted party upholds his commitments his reputation grows; if he breaks his commitments his reputation is damaged, possibly beyond repair (Tullock, 1985). In terms of informal contracts between members of boards, prior shared work experience and reputation effects lead to informal contracts among board members that reinforce the behaviors/norms of the group.

Taken together, the implications of informal contracting suggests that the contracts between the individual members of a firm's board will affect the way in which the board operates, and thus the way the firm is managed leading to the following hypothesis:

H2: The strength of the informal contracts between the members of a firm's board will affect the governance of the firm.

Lippert and Spagnolo (2011) model the influence of social networks in complex settings wherein contracting is necessarily incomplete and network dynamics create multilateral enforcement mechanisms. The authors argue that network influence may be detrimental to welfare maximization by, for example, enabling corruption. They note, however, that dynamics also allow for decreased information asymmetry and improvements in network governance (i.e., parties acting in accordance with the agreed upon objectives of the network). It is unclear, a priori, whether the informal contracting mechanisms created by the network serve to the benefit, or detriment, of a given firm. As previously mentioned, prior literature has discussed the negative consequences of CEO-director social connections (Hwang and Kim, 2009; Nguyen, 2011; Barnea and Guedj, 2009; El-Khatib, Fogel, and Jandik, 2012; among others). CEO-director clustering may exacerbate the problem if members of the closely knit community conform to unity and demonstrate loyalty. If markets recognize this possibility and demand a clustering premium or adjustment, then we would expect a positive relation between network clustering and explicit corporate governance, i.e., as directors become more clustered we would expect to see increases in explicit governance as a signal to markets of boardroom stability and transparency. What is clear is that the influence of informal contracting is conditional upon the objectives of the contractees. More specifically, in environments where external influences on contractees are high and where the costs of adverse reputation impacts of are high, then the amplification effects of informal contracting should act to reinforce positive behavior thus encouraging good governance. However, in environments where external influences are low and where the costs of adverse reputation impacts of are low, then the amplification effects of informal contracting should act to reinforce negative behaviors thus engendering poorer governance. This dichotomous result leads to the following hypotheses:

H3: In environments where adverse reputation costs are high, stronger informal contracting (clustering) will serve to engender good firm governance.

H4: In environments where adverse reputation costs are low, stronger informal contracting (clustering) will serve to engender poor firm governance.

D. Data and Variable Construction

1. Data and Variable Construction

We construct our social network of business professionals using data from BoardEx. For each year from 1999 to 2009, we include all connections formed up to that year in the network, assuming that once a connection forms, it continues to exist[34]. Consequently, there are a total of 11 networks, each corresponds to a year with the number of edges in the network increases monotonically as the time progresses. The types of connections is mostly professional in nature, formed through common work experience, but some can be formed through common education experience or serving as board members of non-profit organization or social clubs. For our primary analysis, we study the social networks of executives for publically traded firms. The data are systematically collected from annual reports and proxy statements to ensure reliability and

[34] Alternative methods to determine inclusion of a past connection, either by restricting the minimum length of time the connection actually existed (3 years or 5 years), or by restricting how recent the connection existed (within the past three years or five years) do not alter the empirical results.

consistency in the collection process. We include other types of connections in our robustness checks.

We represent each yearly network as an undirected, unweighted graph, $G = (V, E)$, where V is the set of vertices with each vertex corresponding to a node, or person, in the network, and E is the set of edges, or connections between individuals. There is an edge between two vertices if and only if the two nodes are connected in the social network. The undirected graph can be represented by an adjacency matrix of size N, where N is the number of nodes or vertices in the yearly network. The element on the ith row and jth column of the adjacency matrix is $A_{ij} = 1$ if there is an edge between nodes i and j, and 0 otherwise. In the network, two nodes can be connected either directly if there is an edge between them, or indirectly if the information can flow from one node to the other by using other nodes in the network as intermediate relays. There might be more than one paths connecting nodes. The connection between two nodes is stronger if the number of paths between them is larger. Two nodes are disconnected if there is no path connecting them. The clustering operation will group nodes that are densely connected into the same cluster, so that, there are a relatively large number of paths between any node pairs inside a cluster and a relatively few (if any) paths between nodes of different clusters.

The next section provides technical details of how we detect social clustering in the network. The method utilized here is computational in nature, only basing on their set of social connections, without any labeling of their actual board positions. Such "blind" classification therefore provides a subjective measurement of one's network position in its own social structure, un-contaminated by one's exact (superior or subordinate) position in each firm.

2. Detection of Social Clustering

The *N* nodes in the network will be divided into different clusters based on their social connections defined by the adjacency matrix. Nodes inside a cluster should be densely connected to each other with a large number of mutual connections, such that the information can easily flow from one node to its peers in the same cluster through a wealth of direct or indirect connections. On the other hand, there should be no or minimum amount of connections between two nodes in two different clusters.

Since the amount of information flow between two nodes can be measured by counting the number of paths between them, one possible way of clustering is to maximize the number of edges used for intra-cluster connections, or minimize the number of edges for inter-cluster connections. This objective can be achieved by maximizing the modularity metric (Newman, 2004)

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta\left(c_i, c_j\right)$$

where $A_{ij} = 1$ if nodes *i* and *j* are direct neighbors and 0 otherwise, $k_i = \sum_j A_{ij}$ is the degree (or, the number of direct neighbors) of node *i*, $m = \frac{1}{2}\sum_{ij} A_{ij}$ is the total number of edges in the network, c_i is the cluster that node *i* belongs to, and $\delta(u, v) = 1$ if $u = v$ and 0 otherwise. The modularity metric measures the difference between two quantities: $Q_1 = \frac{1}{2m}\sum_{ij} A_{ij}\delta\left(c_i, c_j\right)$ and $Q_2 = \frac{1}{2m}\sum_{ij}\frac{k_i k_j}{2m}\delta\left(c_i, c_j\right)$. The first quantity, Q_1, is the percentage of the edges that are used for intra-cluster connections. A good clustering should have a large value of Q_1 such that the number of edges used for intra-cluster connections is large, or equivalently, the percentage of edges used for inter-cluster connections is small. This means that there are only weak connections between clusters. The second quantity, Q_2, is a similar percentage, but calculated for a random network that has the same node degrees as the original network. In the random network, the probability that nodes *i* and *j* are connected is $\frac{k_i k_j}{2m}$. The difference between Q_1 and Q_2 measures how good the clustering is for a particular network. If Q_1 is close to Q_2, then the clustering is not a good one because the same clustering applied to a random network results in a similar intra-cluster edge percentage as the original network.

The exact optimization with respect to the modularity metric has a prohibitively high complexity for networks with large number of nodes. Thus sub-optimum algorithms are required. In this paper, we adopt a two-step clustering method. The first step divides the original network into a collection of disconnected sub-networks, such that there is no connection between any node in one sub-network and nodes in all other sub-networks. The second step performs clustering inside of each sub-network with the iterative clustering algorithm proposed by Blondel et al. (2008). Since there is no connection between any pair of sub-networks, performing clustering inside of each sub-network separately yields the same performance as clustering over the entire network, but with a much lower complexity.

The sub-network division in the first step is performed by identifying the direct and indirect neighbors of a given node. Two nodes are direct neighbors if there is an edge between them, and they are indirect neighbors if they are connected through other nodes. The direct neighbors of a node can be directly obtained by using the adjacency matrix. For example, if $A_{ij} = 1$, then node *j* is a direct neighbor of node *i* and vice versa. Once the direct neighbors of a node are identified, we can locate its indirect neighbors by checking the neighbors of its direct neighbors. For instance, node *i* has a direct neighbor *j*, which in turn has a direct neighbor *k*, then nodes *i* and *k* are indirect neighbors if there is no direct connection between them. We can repeat this procedure until the neighboring relationship among all the nodes is identified. If two nodes are neighbors (either direct or indirect), then they are in the same sub-network. If two nodes are neither direct nor indirect neighbors, they will be placed at different sub-networks. With such a procedure, we can divide the original network with *N* nodes into *K* sub-networks, each with N_k nodes, and $\sum_{k=1}^{K} N_k = N$.

After the division of the original network into *K* disconnected sub-networks, the second step performs clustering for each sub-network separately. Clustering inside a sub-network is performed by using the iterative algorithm proposed by Blondel et al. (2008). The clustering algorithm is summarized as follows.

The clustering operation comprises multiple iterations. Each iteration consists of two phases. In the first phase, each node forms its own cluster of size 1. For a given node *i*, we can calculate the change in modularity if it is moved from its current cluster c_i to a new cluster c_j, where node *j* is a direct neighbor of node *i*. Denote the modularity change caused by moving node *i* from cluster c_i to cluster c_j as $\Delta Q_{i \to j}$. The modularity change is calculated for all the direct neighbors of node *i*. If all the modularity changes are negative, then node *i* will remain at its current cluster, because moving node *i* from its current cluster any of the cluster of its direct neighbors will result in a loss of modularity. If any least one of the modularity change is positive, then node *i* will be moved to the cluster that results in the largest modularity change. This procedure is repeated for all the nodes in the sub-network. In the second phase, all the nodes belonging to the same cluster are grouped into a new node, and this yields a new network with the number of nodes equal to the number of clusters in the original network. The weight of the edge between two new nodes equals to the sum of the weights of the edges connecting the two original clusters. Each node also has a self-looping edge with weight equal to the sum weight of all the edges inside the original cluster. The newly formed network will be used as the starting point in the next iteration. This procedure is repeated until no modularity gain can be achieved. At the end, each node i is associated with a cluster c_i.

To summarize, the input of the clustering operation is the network adjacency matrix, which defined the connections between the nodes in the network. The output of the clustering operation is the clustering assignment c_i, for $i = 1, \dots, N$. Figure 1 provides a graphical example of a stylized network with three clusters. Cluster 1 consists of 6 individual nodes and represents the least "complete" cluster of the three, in that, node 6 is not connected to node 4, 1, or 5, Cluster 3 consists of 4 nodes in a "complete" cluster, i.e., each node is connected to all of the others within the cluster. The clustering operation analyzes the network in order to produce a measure of clustering which ranges from -0.5, no clustering, to 1, complete clustering. For example, when the clustering operation is applied to the network in figure 1, a value for Q of .516 is obtained. The clustering assignment will be used to measure the CEO-Director clustering as described in the next subsection.

[Insert Figure 2 about here]

For example, Figure 2 attempts to depict the social network of over 210,000 business professionals in 2000. The graph includes three distinct sets of clusters: (a) a dense core where each cluster is densely connected to almost all other core clusters, (b) "petals" - smaller clusters that are connected to one or two core clusters, and (c) complete isolates very small in size but large by count representing 19,910 individuals unconnected to the giant component, forming the outer ring. Like many complex networks, Figure 2 shows that our empirical network is locally dense and globally sparse. The network is also highly clustered, forming pockets of densely connected individuals within the community most of whom have relatively few links to the outside.

[Insert Table 1 about here]

Table 1 presents summary statistics on the sizes and numbers of clusters in each yearly network. On average, our algorithm detects roughly 4,500 clusters per year, with the average cluster comprising 25 individuals, and the median cluster, 11 individuals. The mean (median) cluster size increases monotonically over the sample period as a result of the assumption that connections are not severed.

3. CEO-Director Clustering at Firm Level

We obtain a list of incumbent CEOs in S&P 1500 firms from ExecuComp, and a matched list of directors for each CEO from RiskMetrics. Based on the results from clustering, each CEO or director is assigned to a cluster. Note that any particular individual can belong to only one cluster in a given year. For each CEO, we can count how many directors in her firm are in the same cluster as the CEO's. We define a metric, Clustering Ratio, C_{rt}, as the number of directors that are in the same cluster as the CEO's divided by the total number of board seats (excluding the CEO should she also serve on the board). The Clustering Ratio is used to measure the degree to which directors of a board belongs to the same social network cluster as the CEO.

We create several indicator variables to categorize the extent of clustering at each firm. C_{50} is set to 1 if a majority of directors belong to the same cluster as the CEO and 0 otherwise. C_{67} is set to 1 when over two thirds of director (satisfying supermajority requirements) resides in the CEO's cluster. Finally, C_{90}, as a measure of extremely clustered board, indicates that over 90% of board members are clustered together with the CEO.

[Insert Table 2 about here]

A first look at the data reveals significant CEO-board clustering at firm level. Extremely clustered board represents 8% of the sample, supermajority clustering represents nearly 30%, and by simply majority count, 40%. In a typical firm, 40% of directors belong to the same cluster as the CEO. 70% of a board resides in the same social cluster as the CEO in a quarter of the sample.

Further investigation shows that clustering patterns vary with the average centrality of the board. Across all four measures of clustering, firms whose boards are characterized by higher average director centrality, have lower CEO-Director clustering. For firms whose board members have high average centrality, i.e., central boards, about 27% of directors share the same cluster as the CEO. In contrast, for firms whose board members have low average centrality, i.e., peripheral boards about 54% of directors share the same cluster as the CEO. Across all firms in the sample, the rate of clustering for peripheral firms is about 1.97 times that of central firms. When we analyze the binary measures of clustering, we see that the prevalence of majority, supermajority, and extremely clustered boards increases monotonically. For C_{50}, C_{67}, C_{90}, the rate of clustering for peripheral firms is 2.7, 3.36, and 6.76 times the rate of clustering for central firms, respectively.

4. Proxy for Reputation Costs

Figure 2 aids to graphically represent our proxy for the degree of potential reputation effects for the members of various boards. In order to capture external influences of the network on network participants, we examine the centrality of the individuals in the network. Ceteris paribus, the actions of highly central individuals are more apparent to other members of the network than members who are not central. Thus, in environments with greater external oversight (i.e., high centrality), the potential for the negative reputation effects of bad behavior are higher than for areas with lower external oversight (i.e., low centrality). To capture this effect, we create a variable, *Periph*, which takes a value of 1 if the average centrality of the board is less than the median centrality of all boards in a given year.[35] Our variable, *Periph*, captures the "core," "petals," and "isolates" in figure 2 discussed previously.

5. Other Key Variables

The purpose of our analysis is to investigate how CEO-board social clustering affects corporate governance. In our primary analysis, the key variable of corporate governance we use is Bebchuk, Cohen, and Ferrell's (2009), *E-Index*. *E-index* is a composite measure based on six Investor Responsibility Research Center (IRRC) provisions of shareholder protections.[36] The measure takes a value between zero and six, with zero (six) being representative of the best (worst) shareholder protections. In addition to using the index itself, we also examine two of the individual components of the index for which data are made available, i.e., the presence of a staggered board and/or poison pill provision.

[Insert Table 3 about here]

We define a list of commonly used control variables in predicting average *E-Index*: *log of total assets* as the natural log of total book assets, *book leverage* as the sum of long-term and short-term liabilities over total book assets, *return on assets* as the net income over total book assets, and *capital investments* as capital expenditures over total book assets. We include the log of *CEO age* as an additional control following Morck, Shleifer, and Vishny (1988).

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[35] As robustness, we also used terciles, quantiles, deciles, and average centrality of the board as a continuous measure; the results were qualitatively similar in all cases. We used above/below the median as our primary measure simply because the interpretation is straightforward.

[36] We thank Lucian Bebchuk, Alma Cohen, and Allen Ferrell for making their data publically available: http://www.law.harvard.edu/faculty/bebchuk/data.shtml. Bebchuk et al. (2009) construct their measure as the summation of six indicator variables which take a value of 1 if a firm has any of the following: 1) staggered board; 2) poison pill provision; 3) golden parachute policy for executives; 4) limits to amend bylaws; 5) limits to amend charter; and, 6) supermajority for mergers.

In additional testing, we examine the relation between the inner workings of the board and clustering. Specifically, we study the relation between clustering and board independence, board business, and board monitoring. Our measure of *board independence* is constructed as an indicator which takes on a value of 1 for boards that have a majority of independent directors and 0 otherwise (Fogel, Ma, and Morck, 2012). Additionally, we look at CEO's total compensation and incentive pay as taken from ExecuComp. Total CEO compensation, *CEO compensation*, is the sum of salary, bonuses, the value of stock and options granted, the value of long-term incentive payouts, and any other compensation grated. Data on executive compensation are from ExecuComp. In regression testing, we take the natural log of total compensation to reduce the non-linearity inherent in CEO compensation. For *performance pay*, we scale the equity-dependent portion of the CEO's total compensation by the total compensation paid to the CEO in that year. The equity component includes long-term incentive payouts, restricted stock grants (fair value stock awards), and the value of options granted.

[Insert Table 4 about here]

Table 4 presents the description and the summary statistics of these variables across relative clustering. Across measures of firm characteristics, differences emerge for both performance and financial characteristics. The average Tobin's Q for firms who are characterized as being relatively less clustered is higher for all three measure of clustering. Firm size, as measured by the natural log of total assets, is higher for less clustered firms for all but the most clustered firms. Book leverage is higher for firms who are less clustered. Capital investments are lower for less clustered firms R&D investments make up an average of 2.5% to 2.9% of a firm's book assets for less clustered firms, but only 1.2% to 1.6% for firms who are relatively more clustered. Summary statistics on ROA suggest that less clustered firms are relatively more profitable, but the difference is not economically significant.

Across measures of governance and board and CEO characteristics/compensation, we find similar differences in firms based on their relative clustering. On average, based on *E-Index*, less clustered boards have worse shareholder protections. However, they have more independent boards. CEO age and tenure are both higher for firms with a relatively higher degree of clustering. Perhaps most striking are the differences in CEO compensation across relative clustering. CEOs of highly clustered firms have lower total compensation, but have higher cash compensation and lower performance based compensation (both is absolute terms and as a percentage of their total compensation). Taken together, measures of governance and board and CEO characteristics/compensation suggests clustering as a potential factor in the heterogeneity of the governance of firms.

[Insert Table 5 about here]

We repeat the analysis of Table 4 and examine the same firm, board, and CEO characteristics, now splitting the sample by the location of the firm in the network, i.e., *Periph*. Periphery located firms have lower Q, are smaller, are less levered, have higher capital investments, are less R&D intensive, and are less profitable than their centrally located counterparts on average. Across all measures of the financial characteristics of the firm, the differences are statistically different at greater than the 5% level. The differences are only economically meaningful, however, for size and R&D. Across measures of governance and board and CEO characteristics/compensation, we find differences in firms based on their relative location. Firms who are relative more centrally located have worse shareholder protections than those who are more peripherally located. However, similar to the differences identified by clustering, they have more independent boards. CEOs of peripherally located firms are older and have longer tenure in their position than their centrally located counterparts. Finally, differences in CEO compensation across *Periph* show a similar pattern to differences across centrality. CEOs of peripherally related firms have lower total compensation, but lower performance based compensation (both in absolute dollars and as a percentage of their total compensation). Finally, CEOs of *Periph* firms are paid a lower percentage of the total compensation paid to the top-five executive of their respective firms (Bebchuk, Cremers, Peyer, 2011).

E. CEO-Board Clustering and Governance

In this section, we provide empirical evidence from OLS panel regressions on the association between CEO-director clustering, firm governance, and board effectiveness. We show that clustering benefits one type of firm while hurting another. We find evidence that firms in environments where the potential for adverse reputation costs to its board of directors are high (low), benefit (suffer) from CEO-director clustering. We confirm the results of our panel regression by examining CEO-turnover following value destroying acquisitions at the end of this section.

1. Clustering and Governance

We first investigate whether a board dominated by directors who cluster in the CEO's social network affect firm governance and CEO entrenchment. Given the difficulty in capturing a firm's governance with one-simple variable, our methodological approach is to examine commonly used proxies for governance, both composite measures and individual measures, in our tests. Bebchuk, Cohen, and Ferrell (2009) provide one such measure. Bebchuk et al. examine the findings of Gompers, Ishii, and Metrick (2003) to examine which, of the 24 provisions identified by Gompers et al., are the drivers of the inverse relation between poor shareholder protections and firm value. Bebchuk et al. find that six individual provisions are driving the results of Gompers et al. and develop an entrenchment index, i.e., *E-Index*, accordingly. For robustness, we examine the individual components of the E-Index for which we have data to see which components, if any, are associated with CEO-director clustering. In this section, we are asking the question, "Is having a majority of directors in a CEO's social cluster associated with poorer shareholder protections?"

[Insert Table 6 about here]

We first examine the effects of network clustering on the firm governance (*E-Index*) of firms using a panel ordinary least squares framework with heteroskedasticity-robust standard errors clustered at firm level. For this test, all control variables and the measures of clustering are lagged on time-period to better capture the dynamics of the process. Column (1) of Table 6 uses our continuous measure of clustering, $C_{\underline{rt}}$, whereas columns (2)-(4) use C_{50}, C_{67}, and C_{90}, respectively. Across all four specifications, the coefficient estimates on the clustering and *Periph* variables are negative and statistically significant. These results suggest that, on average, having a relatively highly clustered board and having a periphery located board are associated with better shareholder protections. The negative coefficient estimates on the clustering variables are consistent with the conjecture that firms who are relatively highly clustered, in environments where the potential for adverse reputation costs to board members is high, benefit from CEO-director clustering. The negative coefficient estimate on periphery is also consistent with the conjecture that reputation effects mitigate agency problems. The coefficient estimates on the interaction terms between our clustering variables and periphery tell the other side of the story.

Across all four specifications, the coefficient on the interaction term is positive and statistically significant at better than the 1% level. Further, the coefficient estimate increase monotonically as firms become relatively more clustered. The positive coefficient estimates supports the conjecture that clustering acts to engender agency problems for firms whose board faces relatively lower costs to engaging in self-dealing. Taken together, these results support the notion that informal contracts between network participants affect the behavior of clusters within the network, i.e., for firms whose boards are (are not) centrally located clustering acts to mitigate (intensify) agency costs.

The E-Index is a composite measure of firm governance. As such, analyses which rely solely on it to capture firm governance overlook the differential effects of the various components. In this section, we look at the two components for which data were readily available: 1) whether or not the firm has a poison pill provision; and, 2) whether or not the firms has a staggered board provision. A significant body of extant literature has documented an inverse relationship between the presence/adoption of a poison pill provisions and firm value.[37] As for staggered boards, Bebchuk and Cohen (2005) find that staggered boards are associated with an economically significant reduction in firm value. They show that this effect is strongest for firms whose staggered board provision is in the firm's charter and therefore out of the reach of shareholders to amend. For our analysis, we use data from GMI Ratings to construct indicator variables which take a value of one if a firm has either a poison pill provision or a staggered board provision. Table 7 provides the results of this testing.

[Insert Table 7 about here]

Panel A provides the results of probit regressions testing for the presence of poison pill. Across all four specifications, only the coefficient estimates on *Periph* are statistically significant. These negative coefficient estimates are consistent with the conjecture that reputation

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[37] Ryngaert (1988), Brickley, Lease, and Smith (1988), Davis (1991), and Agrawal and Knoeber (1996), among others.

effects mitigate agency problems. Despite the lack of statistical significance [excluding the results in column (2)], the coefficient estimates on the interaction terms are positive; this is weak evidence in support of the entrenchment effects of being highly clustered and isolated from network effects. The results of our staggered board regressions are much more pronounced.

Across the four specifications which use our staggered board indicator as the dependent variable, the coefficient estimates on the interaction term between the various clustering variables and *periph* are positive and statistically significant at better than the 5% level. Additionally, the main effects for the clustering variables and the periph variable are negative in all specifications and are statistically significant in two of the four specification for clustering and in all specifications for *periph*. Taken together, these results provide evidence supporting the hypothesis that clustering is beneficial for firms whose directors face high potential adverse reputation costs to bad behavior and is harmful for firms whose directors are isolated in the network.

2. Clustering, CEO Compensation, and CEO Entrenchment

The E-Index and its components capture one facet of the overall governance of a firm. In this section, we examine the relation between clustering and various proxies for CEO power and control. More specifically, we investigate the relation between clustering and various CEO compensation metrics and proxies for CEO power. Jiraporn, Kim, and Davidson (2005) study the link between poor shareholder protections and CEO compensation. They show that firms with relatively weaker shareholder rights have CEOs with higher pay and lower performance-pay sensitivity. In addition, they document that CEOs of firms with stronger anti-takeover provisions enjoy even more generous pay. When Jiraporn et al. examine performance pay, they document an asymmetric response of CEO to shareholder wealth. When shareholder wealth rises, CEO rises in step. However, when shareholder wealth falls, CEO compensation does not decline when shareholder rights are weak. Building on the results of Jiraporn et al., we examine the relation between clustering and CEO total compensation and performance pay. The results of this testing is presented in Table 8.

[Insert Table 8 about here]

Panel A of Table 8 presents the results from panel tests using ordinary least squares framework with heteroskedasticity-robust standard errors clustered at firm level. Other controls include ln(CEO Age), ln(Total Assets), Book Leverage, ROA, and Investments. As with prior tests, all independent variables are lagged one time period. Across all four specifications, we find that periphery firms pay less on average and that this difference is statistically significant at better than the 1% level. Further, we find no relation between clustering, nor clustering interacted with *periph*, and total CEO compensation; the coefficient estimates on clustering and its interaction with *periph* hover around zero for all specifications. These results suggest that CEOs of peripheral-clustered firms are not, or do not, extract rents in the form of excess compensation from the firm they manage. However, examining total compensation only tells one aspect of the compensation story. In Panel B, we examine the fraction of CEO pay that is sensitive to fluctuations in equity value. The dependent variable in these tests, *CEO Performance Pay*, is the ratio of equity-based compensation to total compensation. Across all four specifications, the coefficient estimates on clustering, *periph*, and their interaction are negative and statistically significant. Further, the coefficient estimates on the interaction decrease monotonically with the relative clustering of the firm, i.e., for majority clustered firm the coefficient estimate is -.9% whereas it decreases to -2.2% for extremely clustered firms. The fact that the estimates are negative and that they increase with clustering is consistent with the entrenchment effects of highly-clustered firms in environments with low potential reputation costs.

Another way to examine the CEO compensation story is to look at the relative power or control garnered by the CEO using compensation as a proxy. Bebchuk, Cremers, and Peyer (2011) investigate the relation between CEO Pay Slice, the ratio of CEO total compensation to the total compensation paid to the top-5 executives of the firm, and firm value, performance, and behavior. They find that CEO Pay Slice is inversely related to firm value, profitability, and performance sensitivity of CEO turnover. Bebchuk et al. (2011) conclude that CEO Pay Slice serves as a good indicator of agency problems. We use their measure to examine the relation between it and clustering.

[Insert Table 9 about here]

Table 9 presents the results from panel tests using ordinary least squares framework with heteroskedasticity-robust standard errors clustered at firm level. Other controls are the same as our prior tests on compensation. For all four measures of clustering, the coefficient estimates are negative and statistically significant suggesting clustering is, on average, associated with a reduced CEO Pay Slice. The estimates on *Periph* are negative, but are only marginally significant. The interesting result from Table 9 is the fact that the estimates on the interaction term between clustering and Periph are positive and statistically significant for all four specifications. This results suggests that CEOs of periphery related firms who are also relatively highly clustered are able to garner a greater fraction of the total compensation paid to the top-five executives. To the extent that this variable captures dynamics related to firm governance, the positive coefficient estimates are consistent with the conjecture that clustering is associated with poor governance in environments where the potential for adverse reputation costs to board members are low.

3. Clustering and Board Effectiveness

We now turn to testing on the effectiveness of the boards themselves. Are clustered board members effective monitors of CEO actions? Or, are boards complicit in the agency problems that result from the separation of ownership and control? One way to assess board effectiveness is to investigate some of the board characteristics identified in prior literature to affect governance. We address the association between social network clustering and board effectiveness and the impact on firm value in the following section.

First, we investigate the relation between CEO-director clustering and board independence. The literature on board independence and firm valuation is somewhat mixed.[38] Despite the lack of findings of a relation, prior literature documented a somewhat stronger positive association between director independence and governance. For example, Beasley (1996) examines the relation between board composition and financial statement fraud and finds that firms without instances of financial fraud have significantly higher percentages of independent directors than firms with instances of fraud. Hermalin and Weisbach (1998) model the board selection process and provide a model in which board effectiveness is a function of its independence. A second dynamic of boards to consider is their size. Jensen (1993), Yermack (1996), Eisenberg, Sundgren, and Wells (1998), and Coles, Daniel, and Naveen (2008), among others, find that board size is related to valuation. The first three argue that this relationship is negative, i.e., firms with larger boards have lower valuation. Coles et al. (2008) argue that this relationship is a function of firm complexity. Jensen (1993) sums up the problem of a large board

[38] See Dalton, Daily, Ellstrand, and Johnson (1998) for a survey of this literature.

stating that '…they are less likely to function effectively and are easier for the CEO to control.' We examine the relation between clustering, board independence, and board size. The results of these tests are presented in Table 10.

[Insert Table 10 about here]

Panel A of Table 10 provides the results of probit regressions with robust standard errors clustered at the firm level. All independent variables are lagged on time period. Across all four specifications, the coefficient estimates on both *Periph* and its interaction with clustering are negative and significant suggesting that periphery firms have less independent boards and that the effect if stronger for clustered-periphery firms. To the extent that independent boards are better monitors, this result is consistent with entrenchment story presented in prior tables. Panel B of Table 10 provides the results of ordinary least squares regression with robust standard errors clustered at the firm level. In all four specifications, clustering and its interaction with *Periph* are positive and statistically significant. The fact that the interaction term is positive and significant indicates the marginal effect of being clustered on the periphery is positively associated with increases in board size.

4. Clustering and CEO Turnover

Our prior analyses rely, largely on panel regressions to identify the relation between clustering and firm governance. In this section, we analyze the association in an event framework. The labor market for managers operates as a restraint on the managers of firms acting to incentive with both 'carrots' and 'sticks'. In an optimal setting, the labor market will restrain managers through the threat of being fired and the negative reputation effects that result and, at the same time, reward managers who perform well through the promise of higher wages or a better position (Weisbach, 1988; Jensen and Murphy, 1990). This outcome, however, assumes that the board of directors is optimally acting in the best interests of the shareholders. For example, if the threat of forced turnover is ameliorated by the fact that the board acts to insulate top managers from the labor market, then the threat of being fired and the negative reputation costs that result will be ineffective mechanisms in restraining agency costs.

In this section, we examine the extent to which social clustering and reputation costs insulate/expose CEOs from disciplinary turnover following value-destroying acquisitions. Specifically, we follow the methodology of Lehn and Zhao (2006) and El-Khatib et al. (forthcoming) in modeling the likelihood that a CEO faces a disciplinary turnover in a five year window following the first acquisition announcement by the firm's CEO during our sample period. Collectively, Lehn and Zhao (2006) and El-Khatib et al. (forthcoming) find that the announcement window cumulative abnormal return is a significant determinant in models predicting disciplinary CEO turnover. In other words, CEOs of poorly performing acquisitions are more likely to face disciplinary action. Additionally, El-Khatib et al. (forthcoming) show that the likelihood that a CEO of a poorly performing acquisition will face disciplinary turnover is negatively related to the CEO's centrality. We follow the framework Lehn and Zhao (2006) and El-Khatib et al. (forthcoming) adding social clustering and the average centrality of the board (i.e., *Periph*) to their analysis to examine their interplay.

Given that we examine the five year window following the announcement for instances of CEO turnover, our sample period of CEO disciplinary turnovers covers acquisitions that take place from January 2000 through December 2005. Following prior studies, we make three additional restrictions to our turnover sample. Firstly, we require that our acquisitions involve publically traded firms, both acquirer and target, with data on CRSP and Compustat. Secondly, if there is more than one acquisition in the sample for a given CEO-firm combination, we keep only the first acquisition. Finally, we restrict the sample to include only those acquisitions where the target firm's market value is at least 10% of the market value of the acquiring firm. Data on CEO turnover come from Execucomp. To identify whether or not a CEO remains with the firm five years after the acquisition announcement, we compare the CEO in the year prior to the acquisition to the CEO five years following the acquisition. Our methodology dies generate a list of CEO turnovers, however, it does not indicate whether or not the turnover was forced. To get this information, we follow Lehn and Zhao (2006) in defining turnovers which are due to disciplinary action, i.e., turnovers which are due to internal governance, takeovers, or bankruptcy. Data on internal governance turnovers, turnovers due to takeovers, and turnovers due to bankruptcy in compiled in two distinct ways. Firstly, data on internal governance turnovers comes from Execucomp's "*Reason*" variable which captures the reason for a departure. In the event that the data is missing, we use the CEO's age as a proxy, i.e., if the CEO is less than 65 when she is replaced, we classify this as a disciplinary turnover.[39] Secondly, to ascertain whether or not a CEO turnover is due to a takeover or bankruptcy, we examine whether or not a CEO retains her job following the takeover (bankruptcy). The final sample consists of 186 acquisitions.

We run the following probit model on the turnover sample:

$$P(Turnover = 1) = \alpha + \beta_1 * Clust + \beta_2 * Periph + \beta_3(Clust * Periph) + \boldsymbol{\delta} + e_i$$

where the dependent variable takes a value of one if there is a disciplinary CEO turnover in the five-year window following the acquisition, *Clust* is one of our four measures of clustering depending on the specification, *Periph* is an indicator variables that equals one if the average board centrality is below the median, $(Clust * Periph)$ is their interaction, and **δ** is a matrix of

[39] Our results are robust if we exclude this assumption.

control variables including the average percentile centrality of the CEO, the ROA of the firm in the three years before (after) the acquisition, the age of the CEO in the year of the announcement, and the CEO's tenure in her current position at the time of the announcement. [40] The results of this analysis are presented in Table 11.

[Insert Table 11 about here]

Coefficient estimates on our control variables are consistent with prior literature. Consistent with the findings of Lehn and Zhao (2006) and El-Khatib et al. (forthcoming) the coefficient estimates on *CAR[-3,+3]* are negative and significant in all four specifications. Further, our estimates on CEO centrality are positive and significant consistent with El-Khatib et al. who find that higher CEO centrality, ceteris paribus, insulates managers from the labor market. The diagonal in the top half of Table 11 provides the main results of our testing. Across all four specifications, the coefficient estimates on our clustering variables are positive while the estimates on *Periph* are negative. However, they are all statistically indistinguishable from zero. In contrast, the interaction between clustering and Periph is negative and statistically significant in all four specifications. The negative and statistically significant estimate on the interaction suggests that CEOs of clustered firms whose boards have low average centrality, are less subject to the labor market.

Most central to our story, however, is the triple interaction of clustering, *Periph*, and *CAR*. The coefficient estimate on the triple interaction is positive and significant across the four specifications. This result suggests that, although a reduced car increases the likelihood that a

[40] We follow El-Khatib et al. (forthcoming) and Fogel, Jandik, McCumber (working paper) in calculating CEO centrality. We first calculate four measures of CEO centrality, degree-centrality, betweeness-centrality, closeness-centrality, and eigenvector-centrality. We then calculate the percentile rankings for each measure and average across the four for a given CEO in a given year.

CEO faces disciplinary action, this result is ameliorated in the cases where the CEO is managing a clustered firm whose boards has a low potential for adverse reputation costs. Taken as a whole, these results suggest CEOs of clustered firms on the periphery are insulated from the managerial labor market and tend to retain their jobs following a poorly performing acquisition.

F. Conclusion

Using data from BoardEx on over 380,000 business professionals and approximately 12 million pairs of unique social connections, we use a novel approach to detect the community structures, or "clusters", of the network. Inclusion within these tight-knit local communities acts as an informal contracting mechanism amongst the members of the group wherein behavior consistent with the group's ideals is rewarded while behavior contrary is punished. This, we argue, acts as complement to traditional governance affecting agency costs and producing asymmetric consequences for the shareholders of the firm, i.e., in some instances clustering leads to desirable outcomes for shareholders while in others it leads negative outcomes. We separate these dichotomous outcomes by conditioning the board of directors on their relative, network-imposed adverse reputation costs and find that clustering is beneficial when the potential for adverse network effects is high and harmful when the potential for adverse networks effects is low.

We construct several variables of CEO-director clustering to measure the degree to which board members belong to the same cluster as their respective CEOs. Our evidence shows that the architecture of the network itself matters. Controlling for CEO and directors' bilateral connections, we show that the degree to which a CEO and her directors overlap in social communities affects the governance of the firm and that these effects are conditional upon the potential for adverse reputation costs faced by the members of the board. For firms whose boards face relatively lower potential adverse reputation costs to bad behavior, clustering is associated with poorer governance and greater rent-extraction by managers. For firms whose boards face relatively higher potential adverse reputation costs to bad behavior, clustering acts as an implicit enforcement mechanism complementary to explicit firm governance. Specifically, when we examine the relation between clustering and various measures of corporate governance, we observe higher managerial entrenchment, in the forms of reductions in shareholder protections, lower CEO performance-pay sensitivity, lower board independence, greater board size, and a reduction in functionality of the executive labor market.

We contribute to the corporate finance literature in several ways. First, our results add to the literature on pairwise, or bilateral, connections by suggesting that the bilateral connection alone does not capture the entirety of the social relationships within a network. The existence of a pairwise connection may simply indicate the presence of a relationship, either in the past or at present, but the strength of the relationship is unknown. On the other hand, belonging to the same cluster is more descriptive of the strength of the relationship, i.e., each cluster represents a social community in which one's relationship to others within the cluster is much stronger than that toward anyone outside the cluster. Relationship within these tight-knit local neighborhoods imposes stronger informal, or implicit, contracts among members within the cluster

Second, we extend the existing literature on network clustering to business executive social networks. The detection of social clusters allows us to analyze the structure or robustness of the CEO's social relationships to the directors. By grouping CEOs and directors into closely knit social neighborhoods in which they share more than just common work experience, but also mutual friends, information, and maintain closer relationships, we can examine the benefits of the network itself.

We also contribute to the extant literature which examines the effects of network influences on firm outcomes. We show that the degree to which a CEO and her directors overlap in social communities affects the governance of the firm and that these effects are conditional upon the potential for adverse reputation costs faced by the members of the board. For firms whose boards face relatively lower potential adverse reputation costs to bad behavior, clustering is associated with poorer governance and greater rent-extraction by managers. For firms whose boards face relatively higher potential adverse reputation costs to bad behavior, clustering acts as an implicit enforcement mechanism complementary to explicit firm governance.

We welcome additional work in this area to further our understanding of how social relationship modifies the behaviors of connected parties, and affects financial decision making. The research in this field has just begun, with ample room to find new insights.

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Figure 1: Clusters in the Network

This figure provides an example of clustering in a network with 15 nodes and 60 links. The numbered nodes represent individuals, and the links between individuals are their social connections. Individuals within the clusters are densely connected, and those belonging to different clusters are only sparsely connected. As a result, the majority of the links are connecting nodes in the same cluster. Clusters are identified following a procedure that is similar to the one outlined in Blondel, Guillaume, Lambiotte, and Lefebvre (2008), with details given in Section 3.

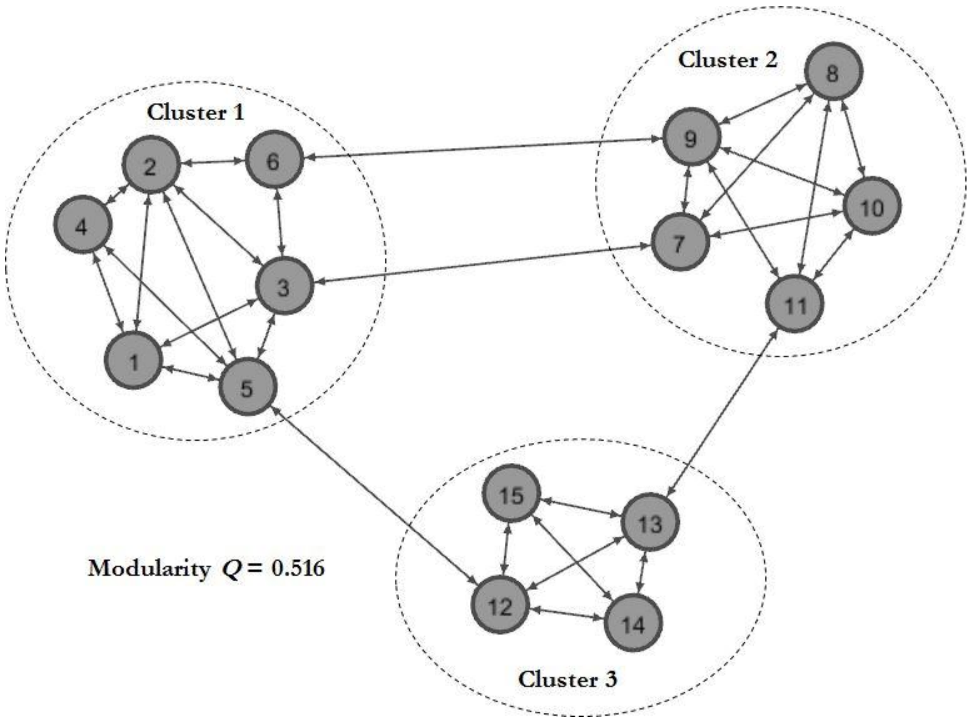

Figure 2: Graphical representation of CEO and director network

Figure 2 attempts to depict the social network of over 210,000 business professionals in 2000, shown in clusters that minimize the number of inter-cluster connections and maximize the number of intra-cluster connections, using the Louvain algorithm for community detection in large networks (Blondel, et al., 2008). The graph includes three distinct sets of clusters: (a) a dense core where each cluster is densely connected to almost all other core clusters, (b) "petals" - smaller clusters that are connected to one or two core clusters, and (c) complete isolates very small in size but large by count representing 19,910 individuals unconnected to the giant component, forming the outer ring. See also Fogel and Zinoviev (2014) for further details.

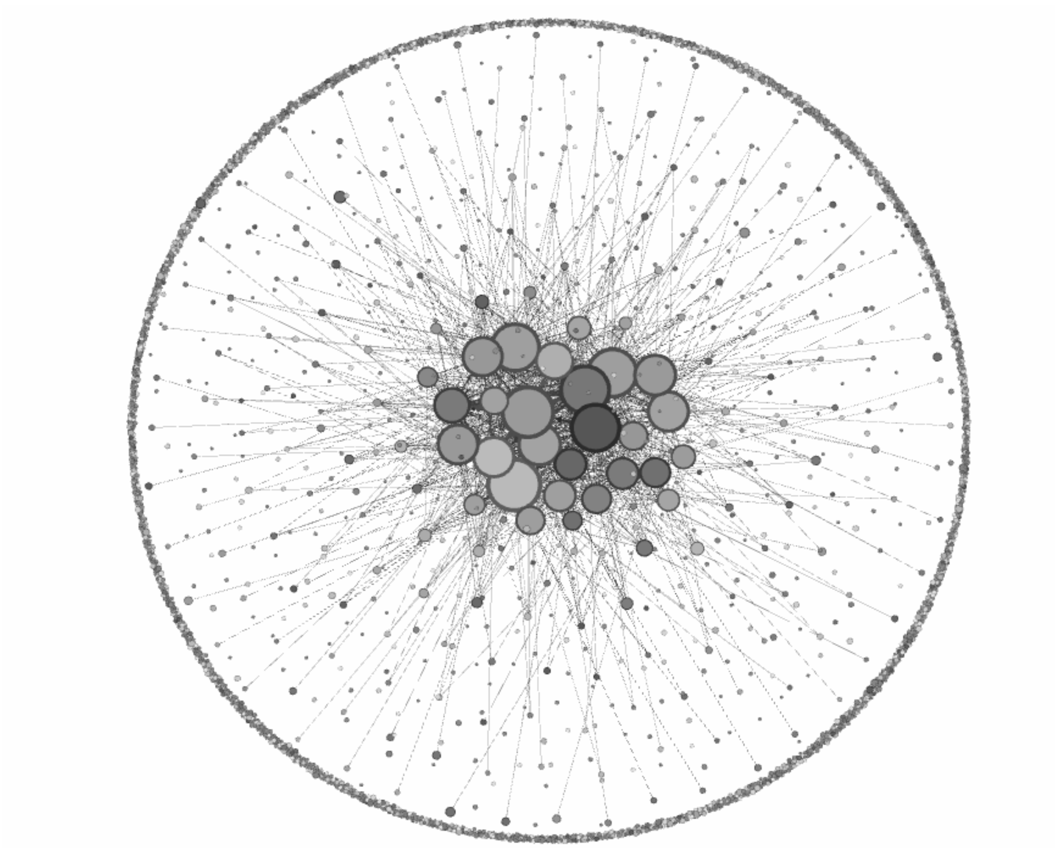

Table 1: Summary Statistics of Clusters in the Network

This table tallies the clusters in the social network of business professionals for each year from 1999 to 2009. **N** is the number of clusters, and distribution statistics (mean, sd, min, max, p25, p50, p75) are describing the size of each cluster.

Year	N	Mean	SD	Min	Max	p25	p50	p75
1999	4416	16.4	45.5	1	1189	3	8	15
2000	4438	18	56.7	1	2462	3	9	17
2001	4469	19.6	74.3	1	3658	3	9	18
2002	4491	21.1	69.3	1	1926	3	10	19
2003	4457	22.8	90.2	1	4207	3	11	20
2004	4391	24.8	95	1	3219	3	12	21
2005	4523	25.9	84.6	1	2236	3	12	23
2006	4474	28	101.6	1	3748	3	13	25
2007	4580	29.3	124	1	6413	3	14	26
2008	4627	31.8	98.3	1	2404	3	15	28
2009	4693	33.3	122.8	1	5454	3	16	30
Total	49559	24.7	91.1	1	6413	3	11	22

Table 2: Summary Statistics on CEO-Director Clustering

This table presents summary statistics of Clustering Ratio (C_{rt}), defined as the number of directors sharing the same social cluster as the CEO as a percentage of total director count, and Clustering indicators (C_{50}, C_{67}, C_{90}) taking the value of 1 if more than 50%, 67%, or 90% of directors share the same social cluster as the CEO and 0 otherwise. "Total" represents the full sample whereas "Central" and "Peripheral" represent boards with high and low average centrality of firms for each year from 1999 to 2010, respectively.

		C_{rt}	C_{50}	C_{67}	C_{90}
Total	N	13933	13933	13933	13933
	Mean	0.401	0.398	0.299	0.080
	Median	0.4	0	0	0
	Std. Dev.	0.342	0.490	0.458	0.272
	p5	0	0	0	0
	p25	0	0	0	0
	p75	0.7	1	1	0
	p95	1	1	1	1
Central	N	7117	7117	7117	7117
	Mean	0.272	0.217	0.131	0.021
	Median	0.182	0	0	0
	Std. Dev.	0.281	0.412	0.337	0.143
	p5	0	0	0	0
	p25	0	0	0	0
	p75	0.5	0	0	0
	p95	0.8	1	1	0
Peripheral	N	6816	6816	6816	6816
	Mean	0.535	0.587	0.475	0.142
	Median	0.625	1	0	0
	Std. Dev.	0.347	0.492	0.499	0.350
	p5	0	0	0	0
	p25	0.2	0	0	0
	p75	0.833	1	1	0
	p95	1	1	1	1

Table 3: Summary Statistics on Financial and Corporate Governance Variables

Table 3 presents key financial measures and corporate governance variables used in the analysis. The variables are defined in the second column, before summary statistics are presented.

Variable	Definition	N	Mean	S.D.	P25	P50	P75
Tobin's Q	(Market equity + book assets – book equity)/total book assets	15889	1.543	1.192	0.848	1.193	1.827
ln(Total Assets)	Natural log of total assets in Compustat	15889	7.846	1.675	6.626	7.659	8.905
Book Leverage	Total book liabilities over total book assets	15889	0.225	0.181	0.066	0.212	0.339
Investments	Capex over total book assets	15889	0.049	0.062	0.013	0.032	0.064
R&D	R&D expenses over total book assets	15889	0.024	0.044	0.000	0.000	0.028
ROA	Net income over total book assets	15889	0.126	0.101	0.070	0.121	0.176
E-Index	Entrenchment Index (Bebchuk, et al., 2009)	15889	2.725	1.395	2	3	4
Indep Board	Indicator valued at 1 for having a majority of independent directors and 0 otherwise	13969	0.906	0.292	1.000	1.000	1
CEO Age	Age of the CEO	15889	55.696	7.326	51	56	60
CEO Tenure	Number of years as CEO	15520	7.051	7.379	2	5	10
CEO Centrality	Average of percentile rakings of 4 centrality measures for the CEO	15889	77.296	19.229	65.333	82.333	93
Total Comp.	CEO's total compensation, in thou.	15889	5646.555	10298.250	1498.564	3150.886	6442.850
Equity Comp.	CEO's incentive pay, in thou.	15889	4227.087	9642.213	615.072	1981.311	4880.367
Cash Comp.	CEO's salary plus bonus, in thou.	15889	1419.469	2146.251	635.000	950.769	1501.900
CEO Perf. Pay	Ratio of CEO equity comp. to total comp.	15889	0.582	0.279	0.414	0.651	0.807
CEO Pay Slice	CEO's salary plus bonus, in thou.	14649	0.375	0.126	0.301	0.377	0.446

Table 4: Pairwise Comparisons of Financial and Corporate Governance Variables by Degrees of CEO-Director Clustering

This table presents t-test statistics of firms categorized by the clustering indicators **C_{50}**, **C_{67}**, or **C_{90}**, which take a value of 1 if 50%, 67%, or 90% of the directors belongs to the same social cluster as the CEO, respectively, and 0 otherwise. The variables are defined in Table 3. Statistical significance indicating different group means are indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	C_{50}				**C_{67}**				**C_{90}**			
	0	1			0	1			0	1		
Variable	Mean	Mean	t-test		Mean	Mean	t-test		Mean	Mean	t-test	
Tobin's Q	1.581	1.484	5.029	***	1.567	1.486	3.786	***	1.558	1.370	4.801	***
ln(Total Assets)	7.879	7.794	3.067	***	7.885	7.750	4.470	***	7.836	7.957	-2.199	**
Book Leverage	0.227	0.220	2.342	**	0.228	0.216	3.788	***	0.225	0.219	1.199	
Investments	0.048	0.051	-2.724	***	0.048	0.052	-3.705	***	0.049	0.047	0.847	
R&D	0.029	0.016	18.543	***	0.027	0.016	15.734	***	0.025	0.012	13.665	***
ROA	0.127	0.123	2.364	**	0.127	0.123	2.246	**	0.127	0.113	4.520	***
E-Index	2.797	2.613	8.065	***	2.787	2.574	8.661	***	2.739	2.556	4.190	***
Indep. Board	0.834	0.744	31.401	***	0.826	0.732	29.717	***	0.808	0.688	20.277	***
CEO Age	55.218	56.442	-9.993	***	55.262	56.753	-11.006	***	55.552	57.417	-7.584	***
CEO Tenure	6.249	8.330	-16.041	***	6.296	8.933	-17.590	***	6.796	10.261	-11.583	***
CEO Centrality	84.088	66.700	58.030	***	82.458	64.754	51.870	***	78.794	59.406	28.258	***
Total Comp	6063.996	4995.237	6.610	***	6021.659	4734.953	7.845	***	5745.293	4466.688	4.648	***
Equity Comp	4694.795	3497.338	8.079	***	4634.315	3237.413	9.531	***	4332.205	2970.980	5.547	***
Cash Comp	1369.201	1497.899	-3.374	***	1387.344	1497.540	-2.534	**	1413.088	1495.708	-1.143	
CEO Perf. Pay	0.623	0.518	23.051	***	0.615	0.501	22.816	***	0.592	0.462	15.092	***
CEO Pay Slice	0.383	0.362	9.634	***	0.380	0.362	7.589	***	0.376	0.361	3.413	***

Table 5: Pairwise Comparisons of Financial and Corporate Governance Variables by Periphery

This table presents t-test statistics of firms categorized by the *periph* indicator (average centrality of the board members of the firm), which take a value of 1 if the average board centrality of a given firm is lower than the median board centrality across all firms. The variables are defined in Table 3. Statistical significance indicating different group means are indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	Peripheral			
	0	1		
Variable	Mean	Mean	t-test	
Tobin's Q	1.631	1.455	5.029	***
ln(Total Assets)	8.415	7.276	3.067	***
Book Leverage	0.236	0.213	2.342	**
Investments	0.045	0.053	-2.724	***
R&D	0.033	0.015	18.543	***
ROA	0.127	0.124	2.364	**
E-Index	2.756	2.694	8.065	***
Indep. Board	0.847	0.749	31.401	***
CEO Age	55.000	56.393	-9.993	***
CEO Tenure	5.563	8.588	-16.041	***
CEO Centrality	88.157	66.423	58.030	***
Total Comp	7938.980	3351.532	6.610	***
Equity Comp	6242.164	2209.726	8.079	***
Cash Comp	1696.816	1141.807	-3.374	***
CEO Perf. Pay	0.664	0.500	23.051	***
CEO Pay Slice	0.383	0.366	9.634	***

Table 6: CEO-Director Clustering and E-Index

This table reports OLS regressions of E-Index on clustering ratio or indicators for the degree to which directors belong to the same social cluster as the CEO of the firm, *periph*, and the interaction between clustering and *periph*. Clustering Ratio (C_{rt}) is defined as the number of directors sharing the same social cluster as the CEO as a percentage of total director count, and Clustering indicators (C_{50}, C_{67}, C_{90}) taking the value of 1 if more than 50%, 67%, or 90% of directors share the same social cluster as the CEO and 0 otherwise. *Periph* is an indicator which take a value of 1 if the average board centrality of a given firm is lower than the median board centrality across all firms. Other Controls include ln(CEO Age), ln(Total Assets), Book Leverage, ROA, and Investments as defined in Table 3. Independent variables are lagged one-time period. All regressions control for Fama-French 17 industry classification and year. Robust standard errors are clustered at firm level. *t*-statistics are reported in the parentheses below the coefficients. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	Dependent Variable = E-Index			
	(1)	(2)	(3)	(4)
C_{rt}	-0.486 ***			
	(-8.41)			
C_{rt} x Periph	0.497 ***			
	(6.64)			
C_{50}		-0.291 ***		
		(-7.41)		
C_{50} x Periph		0.334 ***		
		(6.49)		
C_{67}			-0.438 ***	
			(-9.24)	
C_{67} x Periph			0.437 ***	
			(7.59)	
C_{90}				-0.755 ***
				(-6.57)
C_{90} x Periph				0.831 ***
				(6.71)
Periph	-0.284 ***	-0.222 ***	-0.194 ***	-0.155 ***
	(-7.46)	(-6.66)	(-6.19)	(-5.32)
CEO Centrality	0.003 ***	0.004 ***	0.003 ***	0.004 ***
	(3.28)	(4.43)	(4.13)	(5.03)
Intercept	3.296 ***	3.177 ***	3.141 ***	3.150 ***
	(9.29)	(8.97)	(8.88)	(8.89)
Other Controls	Y	Y	Y	Y
Industry/Year Controls	Y	Y	Y	Y
N	13933	13933	13933	13933
Adj - R^2	0.114	0.113	0.115	0.1126

Table 7: CEO-Director Clustering, Poison Pills, and Staggered Boards

This table reports OLS regressions of Poison Pills (Panel A) and Staggered Board (Panel B) on clustering ratio or indicators for the degree to which directors belonging to the same social cluster as the CEO of the firm, *periph*, and the interaction between clustering and *periph*. The dependent variables are binary and take a value of 1 if a firm has a poison pill provision or a staggered board. Clustering Ratio (C_{rt}) is defined as the number of directors sharing the same social cluster as the CEO as a percentage of total director count, and Clustering indicators (C_{50}, C_{67}, C_{90}) taking the value of 1 if more than 50%, 67%, or 90% of directors share the same social cluster as the CEO and 0 otherwise. *Periph* is an indicator which take a value of 1 if the average board centrality of a given firm is lower than the median board centrality across all firms. Other Controls include ln(CEO Age), ln(Total Assets), Book Leverage, ROA, and Investments as defined in Table 3. Independent variables are lagged one-time period. All regressions control for Fama-French 17 industry classification and year. Robust standard errors are clustered at firm level. *z*-statistics are reported in the brackets below the coefficients. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	Panel A: Dep. Var. = Poison Pill (Yes=1)				**Panel B: Dep. Var. = Staggered Board (Yes=1)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C_{rt}	-0.031				-0.104			
	[-.38]				[-1.55]			
C_{rt} x Periph	0.132				0.216 **			
	[1.25]				[2.50]			
C_{50}		-0.042				-0.063		
		[-.76]				[-1.40]		
C_{50} x Periph		0.129 *				0.139 **		
		[1.79]				[2.35]		
C_{67}			-0.043				-0.210 ***	
			[-.61]				[-3.76]	
C_{67} x Periph			0.071				0.236 ***	
			[.83]				[3.50]	
C_{90}				-0.122				-0.282 **
				[-.62]				[-2.02]
C_{90} x Periph				0.063				0.462 ***
				[.30]				[3.08]
Periph	-0.146 ***	-0.142 ***	-0.111 ***	-0.097 **	-0.174 ***	-0.147 ***	-0.133 ***	-0.117 ***
	[-2.84]	[-3.18]	[-2.65]	[-2.46]	[-4.01]	[-3.88]	[-3.72]	[-3.52]
CEO Centrality	0.005 ***	0.005 ***	0.004 ***	0.004 ***	-0.001	-0.001	-0.002 **	-0.001
	[3.99]	[4.24]	[3.85]	[3.63]	[-1.38]	[-1.60]	[-2.16]	[-1.61]
Intercept	-0.371	-0.375	-0.376	-0.390	1.408 ***	1.382 ***	1.358 ***	1.404 ***
	[-.76]	[-.76]	[-.76]	[-.79]	[3.40]	[3.33]	[3.28]	[3.39]
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry/Year Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	7678	7678	7678	7678	9922	9922	9922	9922
Pseudo - R^2	0.093	0.093	0.093	0.093	0.027	0.027	0.028	0.028

Table 8: CEO-Director Clustering and CEO Compensation

This table reports OLS regressions of Total CEO Compensation (Panel A) and CEO Performance Pay (Panel B) on clustering ratio or indicators for the degree to which directors belonging to the same social cluster as the CEO of the firm, *periph*, and the interaction between clustering and *periph*. Total CEO Compensation is total compensation paid to the CEO in a given year. CEO Performance Pay is the equity-based compensation divided by the total compensation. Clustering Ratio (C_{rt}) is defined as the number of directors sharing the same social cluster as the CEO as a percentage of total director count, and Clustering indicators (C_{50}, C_{67}, C_{90}) taking the value of 1 if more than 50%, 67%, or 90% of directors share the same social cluster as the CEO and 0 otherwise. *Periph* is an indicator which take a value of 1 if the average board centrality of a given firm is lower than the median board centrality across all firms. Other Controls include ln(CEO Age), ln(Total Assets), Book Leverage, ROA, and Investments as defined in Table 3. Independent variables are lagged one-time period. All regressions control for Fama-French 17 industry classification and year. Robust standard errors are clustered at firm level. *t*-statistics are reported in the parentheses below the coefficients. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	Panel A: Dep. Var. = ln(CEO Total Comp)				**Panel B: Dep. Var. = CEO Perf. Pay**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C_{rt}	0.030				-0.046 ***			
	(.43)				(-4.46)			
C_{rt} x Periph	0.046				-0.028 **			
	(.46)				(-2.04)			
C_{50}		0.024				-0.035 ***		
		(.50)				(-4.91)		
C_{50} x Periph		0.008				-0.009 **		
		(.12)				(-1.99)		
C_{67}			0.003				-0.032 ***	
			(.04)				(-3.54)	
C_{67} x Periph			-0.005				-0.016 **	
			(-.08)				(-2.44)	
C_{90}				-0.019				-0.083 ***
				(-.12)				(-3.25)
C_{90} x Periph				-0.111				-0.022 *
				(-.66)				(-1.82)
Periph	-0.313 ***	-0.301 ***	-0.291 ***	-0.283 ***	-0.075 ***	-0.083 ***	-0.083 ***	-0.094 ***
	(-4.57)	(-5.19)	(-5.50)	(-5.98)	(-10.69)	(-13.54)	(-14.65)	(-18.37)
CEO Centrality	0.009 ***	0.009 ***	0.008 ***	0.008 ***	0.0022 ***	0.0022 ***	0.0022 ***	0.0022 ***
	(6.85)	(7.07)	(6.47)	(6.12)	(8.23)	(8.71)	(8.58)	(9.03)
Intercept	5.224 ***	5.236 ***	5.242 ***	5.228	0.914 ***	0.915 ***	0.905 ***	0.911 ***
	(9.92)	(9.88)	(9.83)	(9.80)	(13.14)	(13.15)	(13.00)	(13.07)
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry/Year Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	13933	13933	13933	13933	13933	13933	13933	13933
Adj - R^2	0.281	0.280	0.280	0.280	0.243	0.244	0.244	0.240

Table 9: CEO-Director Clustering and CEO Pay Slice

This table reports OLS regressions of CEO Pay Slice (Bebchuk, Cremers, and Peyer, 2011) on clustering ratio or indicators for the degree to which directors belonging to the same social cluster as the CEO of the firm, *periph*, and the interaction between clustering and *periph*. CEO Pay Slice is the CEO's total compensation divided by the total compensation paid to the top-five executives of the firm. Clustering Ratio (C_{rt}) is defined as the number of directors sharing the same social cluster as the CEO as a percentage of total director count, and Clustering indicators (C_{50}, C_{67}, C_{90}) taking the value of 1 if more than 50%, 67%, or 90% of directors share the same social cluster as the CEO and 0 otherwise. *Periph* is an indicator which take a value of 1 if the average board centrality of a given firm is lower than the median board centrality across all firms. Other Controls include ln(CEO Age), ln(Total Assets), Book Leverage, ROA, and Investments as defined in Table 3. Independent variables are lagged one-time period. All regressions control for Fama-French 17 industry classification and year. Robust standard errors are clustered at firm level. *t*-statistics are reported in parentheses. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	Dep. Var. = CEO Pay Slice			
	(1)	(2)	(3)	(4)
C_{rt}	-0.028 ***			
	(-3.20)			
C_{rt} x Periph	0.031 ***			
	(2.70)			
C_{50}		-0.016 ***		
		(-2.74)		
C_{50} x Periph		0.014 *		
		(1.94)		
C_{67}			-0.020 ***	
			(-2.88)	
C_{67} x Periph			0.021 **	
			(2.52)	
C_{90}				-0.042 **
				(-2.11)
C_{90} x Periph				0.050 **
				(2.34)
Periph	-0.014 **	-0.008	-0.008	-0.006
	(-2.39)	(-1.51)	(-1.61)	(-1.28)
CEO Centrality	0.0006 ***	0.0006 ***	0.0006 **	0.0006 ***
	(3.74)	(4.06)	(4.25)	(4.66)
Intercept	0.466 **	0.460 ***	0.458 ***	0.459 ***
	(7.63)	(7.54)	(7.50)	(7.54)
Other Controls	Y	Y	Y	Y
Industry/Year Controls	Y	Y	Y	Y
N	13933	13933	13933	13933
Adj - R^2	0.033	0.033	0.033	0.033

Table 10: CEO-Director Clustering, Board Independence, and Board Size

This table reports OLS regressions of director independence on clustering ratio or indicators for the degree to which directors belonging to the same social cluster as the CEO of the firm, *periph*, and the interaction between clustering and *periph*. *Independent Board* is an indicator which takes a value of 1 if a majority of the board is comprised of independent directors. Clustering Ratio (C_{rt}) is defined as the number of directors sharing the same social cluster as the CEO as a percentage of total director count, and Clustering indicators (C_{50}, C_{67}, C_{90}) taking the value of 1 if more than 50%, 67%, or 90% of directors share the same social cluster as the CEO and 0 otherwise. *Periph* is an indicator which take a value of 1 if the average board centrality of a given firm is lower than the median board centrality across all firms. Other Controls include ln(CEO Age), ln(Total Assets), Book Leverage, ROA, and Investments as defined in Table 3. Independent variables are lagged one-time period. All regressions control for Fama-French 17 industry classification and year. Robust standard errors are clustered at firm level. *z*-statistics (*t*-statistics) are reported in the brackets (parentheses) below the coefficients. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

	Dep. Var. = Indep. Board (Yes=1)				**Dep. Var. = Board Size**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C_{rt}	-0.003				0.392 ***			
	[-.32]				(4.06)			
C_{rt} x Periph	-0.074 ***				0.213 *			
	[-4.53]				(1.74)			
C_{50}		0.000				0.286 ***		
		[-.04]				(4.30)		
C_{50} x Periph		-0.037 ***				0.119 *		
		[-3.45]				(1.82)		
C_{67}			-0.013				0.147 *	
			[-1.37]				(1.66)	
C_{67} x Periph			-0.041 ***				0.127 *	
			[-3.22]				(1.74)	
C_{90}				-0.012				0.360 *
				[-.50]				(1.75)
C_{90} x Periph				-0.098 ***				0.868 ***
				[-3.43]				(3.87)
Periph	-0.062 ***	-0.075 ***	-0.075 ***	-0.083 ***	-0.035	-0.025	0.017	0.051
	[-7.90]	[-11.16]	[-11.93]	[-14.06]	(-.63)	(-.51)	(.38)	(1.15)
CEO Centrality	0.001 ***	0.001 ***	0.001 ***	-0.042 *	0.012 ***	0.011 ***	0.009 ***	0.009 ***
	[4.07]	[5.84]	[5.36]	[-1.68]	(9.76)	(9.27)	(7.98)	(7.74)
Intercept	0.843 ***	0.838 ***	0.829 ***	0.820 ***	-0.736	-0.630	-0.536	-0.519
	[9.67]	[9.61]	[9.49]	[9.43]	(-1.31)	(-1.12)	(-.95)	(-.92)
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry/Year Controls	Y	Y	Y	Y	Y	Y	Y	Y
N	13933	13933	13933	13933	13933	13933	13933	13933
Pseudo - R^2/Adj - R^2	0.112	0.111	0.113	0.117	0.394	0.394	0.392	0.393

Table 11: CEO-Director Clustering and CEO Turnover

This table reports the results of Probit estimation on the likelihood that a firm experiences a CEO turnover (dependent variable equals 1 if there was a turnover) in the five years following an acquisition. The sample is restricted to acquisitions in which both the acquirer and the target are U.S publically traded firms, that took place between January 2000 and December 2005, and for which the target comprised at least 10% of the acquirer's pre-acquisition market value. Dependent variables of clustering are *Clustrtl*, clustering ratio, and indicators for the degree to which directors belonging to the same social cluster as the CEO of the firm. *Periph*, whether the average board centrality if above the median. And, the interaction between clustering and *periph*. *CAR[-3,+3]* is the cumulative abnormal return to the acquiring firm over the window three days before the announcement to three days after. *CEO Centrality* is the average percentile centrality of the CEO across four measures of centrality. *Pre-ROA* (*Post-ROA*) is the return on assets in the three years before (after) the announcement. *CEO Age* is the age of the CEO in the year of the announcement. *CEO Tenure* is the number of years for which the CEO has been in his current position. Clustering and Periph variables are lagged one-time period. All regressions control for Fama-French 17 industry classification and year. *z*-statistics are reported in the brackets below the coefficients. Statistical significance is indicated by ***, **, * for 1%, 5%, and 10% level, respectively.

Table 11: CEO-Director Clustering and CEO Turnover (Cont.)

	Dep. Var. = CEO Turnover (Yes=1)			
	(1)	(2)	(3)	(4)
C_{rt}	0.051			
	[.14]			
C_{rt} x Periph	-0.553 *			
	[-1.76]			
C_{rt} x Periph x CAR	1.9403 *			
	[1.67]			
C_{50}		0.228		
		[.82]		
C_{50} x Periph		-0.670 **		
		[-2.22]		
C_{50} x Periph x CAR		3.2376 *		
		[1.71]		
C_{67}			0.288	
			[.89]	
C_{67} x Periph			-0.660 **	
			[-2.30]	
C_{67} x Periph x CAR			4.0645 **	
			[2.12]	
C_{90}				0.743
				[.88]
C_{90} x Periph				-0.667 ***
				[-2.58]
C_{90} x Periph x CAR				5.3914 **
				[2.54]
Periph	-0.439	-0.092	-0.225	-0.280
	[-.82]	[-.21]	[-.48]	[-.30]
CAR[-3,+3]	-0.954 *	-0.940 **	-0.911 **	-0.894 **
	[-1.90]	[-2.05]	[-2.14]	[-2.01]
CEO Centrality	0.012 **	0.007 **	0.008 **	0.011 **
	[2.15]	[2.06]	[2.52]	[2.37]
Intercept	-1.855	-2.401 **	-2.301 **	-1.945 *
	[-1.55]	[-2.07]	[-2.02]	[-1.77]
Other Controls	Y	Y	Y	Y
Industry/Year Controls	Y	Y	Y	Y
N	186	186	186	186
Pseudo - R^2	0.129	0.133	0.136	0.138

V. Conclusion

In the first essay I show that credit rating changes induce market revaluations of peer firms. The information revelation of the credit downgrade of an intra-industry peer firms leads to price contagion in similar firms. Further, markets overreact at the news of the credit rating downgrade announcement. At the announcement, the valuation of peer firms suffer regardless of their relative transparency. Post-announcement, in contrast, markets correct the indiscriminate price updating exhibited at announcement. The valuations of transparent firms exhibit reversal in the post-announcement period while the valuations of opaque peer firms exhibit momentum, continuing their decline.

The second essay illustrates the uncertainty resolution effects firms exhibit when becoming credit rated for the first time. The revisions in investor beliefs about the adverse selection risks to transacting in the firm's equity that ensue from the credit rating initiation bring about significant changes in the trading behavior of the firm's secondary market equity. By examining the liquidity costs paid by firms at seasoned equity offerings (SEO), we identify the reduction effects that being credit rated has on the costs to SEOs. Firms who are credit rated face lower SEO costs both in terms of investment bank fees as well as market valuations.

The third essay examines the effects of information propagation and fidelity in the context of firm management. Using a database which covers the social networks of business executives, I investigate the effects that networks impart upon firm governance. The degree to which a CEO and her directors overlap in social communities and the adverse reputation costs they face affects the governance of the firm. For firms whose boards face relatively lower (higher) potential adverse reputation costs to bad behavior, clustering is associated with poorer (better) governance and greater (lesser) expropriation by firm managers.