Do Multiple Credit Ratings Reduce Money Left on the Table? Evidence from U.S. IPOs

(Published in the Journal of Corporate Finance)

Marc Goergen
IE Business School, Madrid, Spain
European Corporate Governance Institute, Brussels, Belgium

Dimitrios Gounopoulos
University of Bath, Bath, UK

Panagiotis Koutroumpis
Queen Mary University London, London, UK

Abstract

Using credit ratings as an uncertainty-reducing mechanism, we provide evidence of the beneficial impact of multiple credit ratings on reducing IPO underpricing and filing price revision. We find that the acquisition of multiple ratings in the pre-IPO period mitigates uncertainty more than the acquisition of a single rating. Multi-rated firms also have higher probabilities of survival than those with a single rating, whereas credit rating levels matter only for IPOs with more than one rating. The IPOs that are awarded the first rating on the borderline between investment and non-investment grades are more likely to seek an additional rating.

Keywords: Initial public offerings (IPOs); credit ratings; IPO underpricing; survivorship

JEL Classifications: G10, G14, G39.

1. Introduction

The role of credit rating agencies (CRA) to both investors and issuers is vital. By serving as an uncertainty-reducing mechanism, CRAs are valuable to investors as they mitigate the risk exposure of the latter. They are also valuable to issuers by reducing their cost of capital. While the list of rated prospective issuers is lengthy, the literature on the effect of multiple ratings on IPO performance is as yet sparse. A plethora of studies[1] suggests that the dissemination of information, or uncertainty reduction, is to the advantage of the least-informed parties in the IPO deal. Thus, it is startling that the acquisition of ratings from a variety of CRAs as a means for a company to signal its superior quality at the IPO remains a field that requires further investigation.

Our research is motivated by Sangiorgi and Spatt (2017a) and (2017b), who argue that multiple ratings are socially optimal if the benefit from the additional rating outweighs the cost of information production. This argument aligns with the "shopping hypothesis" and the "information production hypothesis" of Bongaerts et al. (2012), who state that a) issuers shop for an extra rating in the hope of improving their existing one and b) investors are averse to uncertainty, which is reduced by seeking extra ratings. Liu and Malatesta (2006) were the first to support the facilitating role of CRAs in seasoned equity offerings (SEOs), followed by An and Chan (2008), who conducted a study on IPOs (importantly, both only considered Standard & Poor's (S&P) ratings). Deb and Marisetty (2010) report evidence from India, where since 2007 the regulations have required all IPOs to be graded by at least one CRA. The evidence is inconclusive as Deb and Marisetty (2010) document that IPO grading reduces IPO underpricing after 2007, whereas Jacob and Agarwalla (2012) and Khurshed et al. (2014) do not report any such evidence. We extend the literature by investigating the voluntary acquisition of multiple credit ratings as a means of signaling the superiority of an upcoming offering as well as a control mechanism mitigating the potential upward bias of single ratings (Sangiorgi and Spatt, 2017a).

Another stream of literature (Güntay and Hackbarth, 2010; Bolton et al., 2012) focuses on the association between credit ratings and firm performance for already-listed companies. The perspective we adopt is different as we focus on firms acquiring CRA ratings prior to the IPO, thereby achieving a higher offer price and reducing IPO underpricing. This raises several interesting questions, which we attempt to answer. Do multiple ratings have an impact on IPO performance and the filing price revision? If so, do they facilitate the going-public process more than a single rating? Is there an incremental effect

[1] See, for example, Rock (1986), Beatty and Ritter (1986), Benveniste and Spindt (1989), Welch (1992), Loughran and Ritter (2002), Liu and Malatesta (2006), Bongaerts et al. (2012), Bolton et al. (2012), Kedia et al. (2017) and Griffin et al. (2018).

of investment grading on IPO performance? Are companies with a credit rating on the threshold of the investment grade more likely to acquire an additional rating before going public? Finally, do multi-rated firms have better survival chances than firms with a single rating?

We were inspired by Kedia et al. (2014), who document that Moody's ratings (for both corporate bonds and structured finance products) are significantly more favorable to issuers than S&P ratings. We argue that the existence of independent assessments from several CRAs ahead of the flotation day is an important signal to market participants. To test the validity of this argument, we employ a comprehensive and large sample of U.S. IPOs covering the period from 1 January 1997 to 31 December 2016. Based on information retrieved from Bloomberg, we manually inspect each individual issue for evidence of the acquisition of credit ratings during the eighteen months prior to the first trading day. Comparing the average underpricing of 9.29% for IPOs with multiple credit ratings with the equivalent average of 15.40% for IPOs with a single rating and that of 22.7% for the remaining IPOs, we find support for our hypothesis that multiple credit ratings improve first trading day performance. Importantly, multiple credit ratings have a much greater impact on reducing underpricing than single ratings.

Our study is related to the work of An and Chan (2008), Kisgen (2009), Kisgen and Strahan (2010), Mählmann (2011), Bongaerts et al. (2012), Kedia et al. (2014), Bae et al. (2015), Cornaggia et al. (2017a, 2017b), Sangiorgi and Spatt (2017a), Rabanal and Rud (2018), and Kisgen (2019). The two papers that are most closely related to ours are An and Chan (2008) and Sangiorgi and Spatt (2017a). An and Chan (2008) examine the effects of S&P credit ratings on IPO pricing, while Sangiorgi and Spatt (2017a) develop a framework to understand the existence of multiple ratings and their information content at various levels[2]. Our study is also related to the literature on strategic contracting when the information revealed affects a third party and relates to a wide range of microeconomic issues (Halac, 2012).

We begin our analysis by regressing the level of initial returns on the presence (or absence) of multiple credit ratings, as well as a set of control variables that are commonly employed in the relevant literature. We find that while one credit rating reduces the amount of money "left on the table", two or

[2] Kisgen (2009) focuses on whether firms target credit ratings or leverage levels; Kisgen and Strahan (2010) investigate whether or not the certification of Dominion Bond Rating Service (DBRS) by the U.S. SEC affected the yields on the bonds that DBRS rates; Mählmann (2011) studies whether there is a relationship benefit in credit ratings; Bongaerts et al. (2012) explore the economic role CRAs play in the corporate bond market; whereas Kedia et al. (2014) investigate whether or not Moody's relaxed its rating standards in order to increase its revenues after it went public in 2000. Finally, Bae et al. (2015) and Rabanal and Rud (2018) examine the impact of competition among CRAs on rating quality and truth telling, respectively, while Cornaggia et al. (2017a, 2017b) emphasize the critical role that credit ratings played in the global economy.

three ratings have an even greater effect on reducing IPO underpricing. This result is highly significant at the 1% level.

We then turn our attention from the existence of multiple credit ratings per se to the levels of these ratings. We document a strong association between higher rating levels for multi-rated firms and short-run IPO performance. More precisely, the higher the average credit rating level for companies with multiple ratings, the lower is the level of underpricing. In comparison, the rating level of single-rated issues has at best a weak effect on the level of IPO underpricing. This might be attributed to the more limited information that a single rating conveys. Furthermore, our findings indicate that companies at the investment-grade cut-off (i.e. companies at the borderline between investment and non-investment grades) are more likely to seek an additional credit rating to improve their creditworthiness. One would expect firms with a first rating below the investment grade to receive a second one just above the grade. Surprisingly, the results show that the second rating for non-investment-grade firms typically confirms the first one, while on certain occasions it is even lower. In addition, we document that the greater the credit analyst's optimism – as measured by a stronger second rating – the lower the IPO underpricing. Moreover, firms with a higher second rating experience substantially less underpricing than firms with a higher first rating.

Next, we investigate the impact of multiple credit ratings on the bookbuilding process. We focus on the effect of multiple credit ratings on both the extent and direction of the revision of the filing price during the price discovery period. Interestingly, we identify a negative and highly significant association between multiple ratings and the extent of filing price revisions. Importantly, we do not find that a single credit rating has a negative effect on filing price revisions. This suggests that the existence of multiple credit ratings matters, whereas the existence of a single credit rating is not impactful.

Further, we examine the survival rate of IPO firms with either a single rating or multiple credit ratings. We investigate the extent to which strategic contracting between the informed party (the CRA) and an interested party (the issuer in our case) can secure longevity. We document that companies going public with multiple credit ratings experience higher survival (lower default) rates in the long run.

A methodological challenge for this study is endogeneity. We overcome this challenge in two different ways. First, we use propensity score matching, whereby we match IPO firms with single ratings with IPO firms with multiple ratings based on firm characteristics. Following the matching, we can confirm our results. Second, we use an instrumental variable analysis to extract the exogenous component of the credit rating(s). We introduce the following two instruments. The first is the percentage of firms in the industry with multiple ratings, while the second is the percentage of firms in the industry that went bankrupt in the previous year. Our instrumental variable (IV) analysis confirms our results.

This study offers a number of important and novel contributions to the IPO literature. First, to the best of our knowledge, this is the only study to investigate multiple credit ratings as a means of signaling the quality of an upcoming new equity offering. We find that multiple credit ratings matter because they have beneficial effects on IPO performance and the price revision of the filing price, whereas single ratings have at best a weak effect. Second, our study refines the results of An and Chan (2008), who limit themselves to single ratings, i.e. ratings from S&P, while ignoring ratings from the other two CRAs, i.e. Moody's and Fitch. Although we confirm the results of An and Chan (2008), our findings differ from theirs as follows: First, we document the importance of the credit rating level. Importantly, this effect is only observed for IPOs with more than one credit rating. Second, while we also document that credit ratings reduce the degree of price revision, this effect is evident for IPOs with multiple credit ratings. As the great majority of IPOs belong to the non-investment category, as reflected by a rating at the speculative grade, a single rating will most probably not provide any substantial information. Third, our study examines the survival of IPOs and shows that multi-rated companies have a higher likelihood of survival. Finally, the negative effect of credit ratings on IPO underpricing stems mainly from firms with multiple credit ratings at the investment grade.

The rest of this paper is organized as follows: Section 2 reviews relevant studies from the IPO and credit rating literature; Section 3 develops the hypotheses; Section 4 identifies the data sources, describes the sample selection, and reports the summary statistics while outlining the methodology. We present the outcomes of the empirical analysis in Section 5, and Section 6 examines the survivorship of multi-rated IPOs. To validate our findings, we run a battery of robustness tests in Section 7. We conclude our study with Section 8.

2. Literature Review

2.1. Persistence of Underpricing

In this section we explore the three main explanations for the persistence of underpricing: (a) deliberate underpricing in the premarket, (b) mispricing in the early aftermarket as a result of trading activity, and (c) underwriter price stabilization in the early aftermarket.

We begin with the first explanation, which attributes the initial returns to deliberate underpricing. In particular, Baron (1982) identifies the persistence of the phenomenon of deliberate underpricing as the outcome of a principal-agent conflict. In other words, as the issuing firm (the principal) cannot detect the distribution and marketing efforts of the underwriter (the agent), the underwriter may persuade the issuing firm to accept a low offer price. Further, Loughran and Ritter (2004) introduce an additional agency explanation, i.e. the spinning hypothesis, which is based on a conflict of interests between the pre-IPO shareholders and other decision-makers. It posits that the decision-makers are willing to hire underwriters with a history of underpricing because they receive side payments. Furthermore, Liu and Ritter (2010), in a paper illustrating the magnitude of agency problems that are caused by placing the decision-making power in the firm into the hands of a few executives, document that the average profit from spinning per firm accruing to the executives is approximately $1.3 million.

The second explanation assumes that IPO shares are priced at their intrinsic value in the premarket and attributes the initial returns to trading activity in the early aftermarket by overoptimistic investors and to their valuations. For example, Aggarwal and Rivoli (1990) focus on fads in the IPO market, whereby new issues may not be priced at their fair value in the early aftermarket trading. Further, Ritter (1991) and Loughran and Ritter (1995) explain the initial returns by investors being overoptimistic about the firm's value. This overoptimism results in excess demand for the IPO shares, which pushes up their price and leads to high initial returns in the aftermarket. Aggarwal (2000, 2003), Ellis et al. (2000, 2002), and Ellis (2006) report that flipping activity (consisting of shares being sold in the immediate aftermarket by investors who receive an initial allocation in the offer price period) is not solely responsible for high trading volumes in the early aftermarket. Their estimations indicate that flipping accounts for only 19% of trading volume, whereas 77% of trades are long-term investment activities.

Finally, the third explanation attributes the positive average initial returns to underwriter price support, which in turn leads to a censoring of the return distribution. More specifically, there is a body of literature, such as Ruud (1993), Asquith et al. (1998), and Aggarwal (2000, 2003), which reports that underwriters stabilize the aftermarket prices by purchasing additional shares in case the trading price falls below a certain threshold, which in turn leads to some IPOs being overpriced (i.e. the trading price being lower than the offer price).

2.2. Information-Transmitting Mechanisms

Apart from being instrumental in the price discovery process, underwriters, especially those that are prestigious (see Booth and Smith, 1986; Carter and Manaster, 1990; Carter et al., 1998; Brau and Fawcett, 2006; Chen et al., 2008) may act as a strong, positive signal to the market that the firm going public is worth investing in. In a similar vein, reputable auditing firms (see Titman and Trueman, 1986; Beatty, 1989; Michaely and Shaw, 1995, Venkataraman et al., 2008; Yang, 2013) and venture-capital backing (see Barry et al., 1990; Megginson and Weiss, 1991; Lee and Wahal, 2004; Bradley et al., 2015; Jeppsson, 2018) may constitute third-party certification of the quality of the IPO firm.

Leone et al. (2007) report that 38.1% of the IPO proceeds (for which issuers provide information on how they intend to use them) is designated for debt repayment. In this context, credit ratings, which reveal the ability of companies to pay back their debt, then provide valuable information to investors that the underwriters, the auditors, and the venture capitalists cannot or are not willing to provide[3]. More specifically, a non-investment grade granted by a CRA then suggests issues with the firm's financing and capital structure. Thus, we argue that investors should consider not only the reputation of the underwriter and auditors as well as the backing by a venture capitalist when assessing the quality of an IPO but also the rating provided by a CRA.

The role of credit ratings as an uncertainty-reducing mechanism aimed at outside financiers is well documented in the finance literature. The seminal work of Ederington et al. (1987) reports that corporate managers supply CRAs with proprietary information, which is not known to outsiders. Thus, CRAs serve as information intermediaries whose purpose is to certify the firm's quality without disclosing confidential documents and data. Benabou and Laroque (1992) argue that this process is analogous to the situation that analysts have to deal with when they are asked to recommend stocks to the general public.

Securing a favorable evaluation from a CRA is then of vital importance for a firm, considering that credit ratings not only provide an independent assessment of the firm's creditworthiness but also explicitly serve as a monitoring mechanism for top management. As Pagano and Volpin (2010) point out, CRAs set strict requirements in order to discourage directors from taking too much risk. The inability to comply with these requirements and the consequent downgrading can exert a negative impact on investor confidence. Hand et al. (1992), who examine the monitoring methods of S&P and Moody's, confirm that announcements about reductions in rating levels lead to a substantial and immediate stock price decline. Ederington and Goh (1998) find that this price drop is attributable to the company's credit rating reduction and not to any other cause, such as lower current earnings. Finally, Boot et al. (2006)

[3] Importantly, our empirical analysis reveals that multi-rated firms are less likely to have venture-capital backing, making credit ratings as a signal of firm quality more important. Such firms also have lower percentages of ownership retention by the pre-IPO shareholders, again supporting the greater importance of credit ratings.

argue that because a sufficient number of investors base their investment decisions on credit ratings, other less-informed market participants will follow suit.

2.3. IPO Underwriters and their Role in Pricing IPOs

The price determination for a new equity issue takes place under uncertainty. Accordingly, Rock (1986) and Beatty and Ritter (1986) argue that outsiders feel insufficiently informed about the IPO firm's prospects and therefore request a price discount. One of the key tasks of the IPO underwriters then becomes eliciting information from better informed investors before setting the price and taking the company public.

However, revealing positive information about the issue to the underwriter is not in the interest of the informed investor. Indeed, revealing such information would cause an increase in the offer price and hence reduce the profit for the informed investor. Even worse, it is in the interest of the informed investor to mislead the underwriter by misreporting positive information and hence push the offer price down rather than up. The underwriter then needs to create a mechanism that incentivizes informed investors to disclose their information truthfully.

Benveniste and Spindt (1989), Benveniste and Wilhelm (1990), Spatt and Srivastava (1991), Busaba et al. (2001) and Bubna and Prabhala (2011) argue that bookbuilding, subject to specific conditions, is such a mechanism. As the underwriter has discretion over how many shares are allocated to each investor, it then allocates relatively more shares to investors who revealed positive information about the issue by bidding at a high price while allocating fewer shares to investors who bid at a lower price.

Finally, given that the IPO market is a repeated game, i.e. underwriters and institutional or informed investors deal with each other repeatedly, underwriters can exclude investors that have not truthfully revealed information in the past from future IPOs. In turn, this would give a pricing advantage to underwriters that are more active in the IPO market.

3. Hypothesis Development

In this section we develop our hypotheses. Even though the studies outlined above confirm the role of credit ratings as effective and credible signals of firm quality, spectacular failures of companies with very high credit ratings, together with the 2008 sub-prime mortgage crisis, have raised doubts about the objectivity and validity of CRAs' evaluations. Indeed, the three leading U.S. rating agencies were severely criticized for misleading investors in the aftermath of the 2008 financial crisis. U.S. House Representative Jacqueline Speier squarely put the blame on CRAs when she questioned Moody's top management in a 2009 congressional hearing[4]:

"*You rated AIG and Lehman Brothers as AAA, AA moments before their collapse. Did you take any actions against those who put that kind of a remarkable grade on products that were junk?*"

Still, Bolton et al. (2012) report that potential investors in rated issues are sophisticated and understand the potential conflicts of interest that the CRAs may be facing. The possible lack of trust in the credit rating system stems from the fact that the main source of revenue for CRAs is the firms that are under evaluation as these have to pay to obtain a rating. Consequently, CRAs are incentivized to inflate ratings in a competitive market because they only get paid if an issuer asks the CRA to make the rating public. Furthermore, CRAs create motives for issuers to shop for the best rating given that a significant fraction of investors in bonds trust the CRAs and will therefore not do their own research. As a result, in the oligopolistic market of the CRAs, companies with just one rating are less appealing to investors than those with multiple ratings. Similarly, according to the so-called "rating shopping hypothesis", issuers may seek to maximize their average credit ratings by requesting multiple bids (Bongaerts et al., 2012; Griffin et al., 2013; Flynn and Ghent, 2018).

To date, the effects of multiple credit ratings on IPO performance remain largely unexplored. Addressing this gap in the literature, our paper contends that the acquisition of multiple ratings from the world's leading CRAs (i.e. S&P, Moody's, and Fitch) in the pre-IPO period mitigates uncertainty more than the acquisition of a single rating. Put differently, following Chemmanur and Paeglis (2005), who propose that managers of superior-quality firms seek ways to communicate their company's intrinsic value to lower heterogeneity in investor valuations, we argue that securing multiple ratings significantly enhances outsiders' trust in the firm. This discussion leads to our first hypothesis:

H.1 Multiple credit ratings reduce IPO underpricing more than a single rating does.

[4] More details about the congressional hearing can be found at : https://www.huffingtonpost.com/2009/09/30/credit-rating-agency-anal_n_305587.html?ncid=engmodushpmg00000006

Next, we focus on whether the magnitude of underpricing varies across rating levels. We argue that CRAs not only inform market participants about the company's risk profile but also provide monitoring services via the so-called "watch procedures", which may serve as effective uncertainty mitigators. According to Boot et al. (2005), CRAs strike an implicit "deal" with firm managers whereby the latter agree to take corrective action, when necessary, in order to avoid a reduction in their firm's credit level. Failure to take such action and a consequent downgrading may challenge the confidence of investors and undermine the firm's prospects.

Furthermore, the great majority of IPOs belong to the non-investment category, as reflected by a rating at the speculative grade and the highly speculative grade, suggesting that such IPOs are of high risk. Thus, a single rating will most probably not provide any substantial information. It is then the second rating that may take a plethora of interesting directions. For instance, will it be higher (lower) than the first one and by how many notches? Which one among the top three CRAs awarded the first rating? Finally, from the investors' point of view, is it valuable to have double confirmation of the quality of the firm to which they are about to entrust their money? To sum up, not only the existence of multiple credit ratings but also their level might have an impact on IPO underpricing:

H.2 Ceteris paribus, a higher credit rating level confirmed by multiple credit ratings is related to reduced IPO underpricing.

Securing multiple ratings could also facilitate the price discovery. More specifically, as the bookbuilding process takes place, underwriters promote the new offering during roadshows and attempt to extract proprietary information from informed investors (Benveniste and Spindt, 1989; Hanley, 1993), helping with the price discovery. The magnitude of the price revisions should then be analogous to the information revealed during this procedure. Because credit ratings reduce the information asymmetry around a firm's financial standing, we expect a smaller price revision in their presence. Again, we expect this negative effect to be stronger for firms with multiple credit ratings:

H.3 Ceteris paribus, the existence of multiple credit ratings lowers the degree of price revision more than a single credit rating.

Our final hypothesis focuses on the survival rates of multi-rated IPOs. According to Manso (2013), CRAs should focus not only on the accuracy but also on the effect of their ratings on the probability of survival of the borrower. In this context, Güntay and Hackbarth (2010) claim that multiple ratings are valuable because they mitigate asymmetric information for risk-averse investors, whereas Hilscher and Wilson (2017) report that for credit ratings to be informative indicators of credit risk they have to mirror the main concerns of a risk-averse investor, i.e. the probability of failure and systematic risk. Nevertheless, Bongaerts et al. (2012) suggest that fewer firms may opt for multiple ratings unless the marginal CRA convinces the market that its ratings are useful in terms of providing additional information about credit risk. Finally, Sangiorgi and Spatt (2017a) support the notion that the probability of default decreases with the number of ratings obtained.

We argue that multiple credit ratings mitigate uncertainty about a firm's risks and increase (decrease) the likelihood of survival (default). Hence, we hypothesize that:

H.4 Firms with multiple credit ratings are more likely to survive for longer and are less likely to default than companies with a single rating.

4. Data and Methodology

4.1. Sample Selection Criteria

To construct our sample, we retrieve from the Securities Data Company (SDC) the whole population of new listings on U.S. exchanges for the period of 1 January 1997 to 31 December 2016. Consistent with the previous literature (e.g. Ritter and Welch, 2002; Loughran and Ritter, 2002; Ljungqvist and Wilhelm, 2003; Lowry and Schwert, 2004), we eliminate IPOs priced at less than $5 per share, American Depository Receipts (ADRs), and reverse leveraged buy-outs (LBOs). While allowing financial companies into the sample, we exercise caution and exclude real estate investment trusts (REITs), closed-end funds, special purpose investment vehicles (SIC 6723–6999), and royalty trusts[5]. Finally, we exclude corporate spin-offs as they are part of larger businesses, and hence entail less uncertainty. The remaining sample is merged with the databases of Compustat and the Center for Research in Security Prices (CRSP) from which we obtain accounting and aftermarket data, respectively. This generates a sample of 4,251 IPOs.

[5] Our sample includes 372 financial companies, of which 7% have been awarded a credit rating, whereas the remaining 93% have no rating.

Credit rating data are obtained from Bloomberg. The CRAs covered by this study are the three leading U.S. CRAs, i.e. S&P, Moody's, and Fitch. Of the 4,251 IPOs in our sample, 313 IPOs acquired — or obtained revised — credit ratings before going public. Among the rated IPOs, we identify 135 double and 9 triple-rated issuers[6].

4.2. Sample Selection and Descriptive Statistics

Panel A of Table 1 shows the distribution of the unrated and rated IPOs over the period from 1997 to 2016. The year with the largest percentage of unrated IPOs is 2016, while the year with the highest percentage of rated IPOs is 2002. The stock market crash of 2001, when the dotcom bubble burst, had a considerable impact, reducing the number of IPOs during 2001-2003 by approximately 80% relative to the 1998-2000 period. The IPO market recovered between 2004 and 2007 before plummeting again because of the 2008 financial crisis. Furthermore, comparing the average credit rating level of the two periods before (i.e. 1997-2007) and after (i.e. 2009-2016) the collapse of Lehman Brothers, we find that the average credit rating level of the post-collapse period is approximately 9% lower than during the pre-collapse period (a pattern in line with Dilly and Mählmann, 2016). The market displayed signs of recovery shortly after the crisis (more specifically, from 2010 onwards). Nevertheless, this upward trend slowed down in 2015 because of a lack of momentum in tech offerings as well as the healthcare, financial, consumer, and energy sectors all hitting historical lows.

The CRA that is most preferred by the IPOs is S&P, awarding credit ratings to 77.95% of all rated companies (244 out of the 313 rated IPOs), followed by Moody's with 53.67%, and Fitch with 17.89%. Altogether, 7.36% of the total number of IPOs had ratings from one or more of these three CRAs. Panel B of Table 1 shows the distribution of the credit rating levels. Interestingly, the bulk of ratings range from BBB+ to B- for S&P and Fitch, whereas for Moody's the range is lower, from Ba3 (the equivalent of BBB-) to Caa1 (the equivalent of CCC+). Essentially, the credit ratings for the IPOs are concentrated around the borderline between lower-medium investment grade and non-investment, speculative grade. Thus, the great majority of firms were graded non-investment despite receiving high injections of capital through the listing process. Indeed, firms of the speculative grade raised 45.1% of additional capital to

[6] At this point, it is worth mentioning the percentage of IPO firms by industry that have no debt and thus have no need for a credit rating. More specifically, the Manufacturing sector has the highest percentage of firms with leverage (i.e. 97.10%), whereas the Chemical Products sector has the highest percentage of firms without leverage (i.e. 25.90%).

repay part of their debt while those of the high speculative grade raised 68.1% of additional capital, leaving the remaining 31.9% for all other activities[7].

Moody's appear to be strictest, with 18 ratings (i.e. 5.75% of rated IPOs) in the C categories, followed by Fitch with 9 such ratings (2.87% of rated IPOs) and S&P with only 7 such ratings (2.24% of rated IPOs). Further, S&P rated 150 firms within the B categories (i.e. 47.92%), whereas Moody's rated only 112 companies likewise (i.e. 35.78%), and Fitch just 8 (i.e. 2.56%). Moreover, Panel C of Table 1 documents that for IPOs with two credit ratings (i.e. ratings provided by S&P and Moody's only), S&P and Moody's were the first to be approached in 43.65% (55 out of 126) and 36.51% of cases, respectively. The remaining 19.84% are IPOs that received ratings from both of these CRAs at the same time (see Panel B of Table 1). To conclude, S&P, regardless of the timing of the credit rating conferment, granted a higher credit rating level than Moody's in 52 (41.27%) of the 126 cases. Moody's issued a higher credit level than S&P in only 18 (14.29%) of these 126 cases.

Finally, Panel D of Table 1 reports the timeline of obtaining a credit rating and the corresponding average underpricing. In particular, 62% and 93% of the rated firms obtained at least one rating within the one-year period and the five-year period before going public, respectively. The firms with a shorter period between obtaining a credit rating and going public experienced lower average underpricing than those firms with a longer period (10.31% versus 11.85%). Furthermore, 51% of the multi-rated firms obtained a second rating (before their IPO) within a month of their first rating acquisition. For these firms, the level of underpricing is 2.56 percentage points lower than for those firms with asynchronous credit ratings.

Table 2 reports the summary statistics for the entire sample as well as for the rated and unrated new offerings[8]. Panel A shows that IPOs without credit ratings have the highest average and median levels of underpricing, whereas average and median underpricing is lowest for IPOs with multiple credit ratings; the levels of the underpricing of IPOs with a single rating are somewhere between the former two. The magnitude of the price revision is also highest for unrated IPOs. Further, the mean Tobin's Q ratio, a proxy for the company's competitive advantage (see Chung and Pruitt, 1994), of unrated new offerings is almost three times the means for the single and multi-rated issues, indicating greater growth prospects for firms without a rating. This is partially explained by the substantial growth expectations of

[7] These numbers are not tabulated.

[8] Appendix A reports the detailed definitions of all the variables employed in this study.

IPOs by information technology companies, which rarely have a credit rating. Finally, unrated as well as single-rated firms experience lower levels of investor valuation compared to multi-rated firms.

Panel B of Table 2 documents that unrated IPOs are very different from rated IPOs. For example, unrated IPOs are much smaller, as evidenced by the mean gross proceeds, which amount to only $141 million compared to $346 million for single-rated and $363 million for multi-rated IPOs. This pattern is also evident for average net sales, an alternative measure of firm size. Unrated IPOs are also much younger compared to rated IPOs. In contrast, the difference in age between single-rated and multi-rated IPOs is smaller. Reflecting their lower quality, unrated IPOs are less likely to have a Big Four auditor and prestigious underwriters but are more likely to have venture-capital financing. With respect to overhang, IPOs without credit ratings have higher percentages of ownership retention by the pre-IPO shareholders. They are also more likely to issue only primary shares. Furthermore, the average borrowing costs of single-rated IPOs are higher than those of multi-rated firms, while multi-rated IPOs are less likely to be in the Internet sector. In addition, during the dotcom period firms are more likely to possess multiple ratings, whereas the median of credit rating dispersion is equal to one. Finally, no severe multicollinearity is detected among the variables.

In addition, we investigate whether companies with credit levels between BB and BBB, that is, those that are borderline investment and non-investment grade (referred to as the "CRL cut-off" in what follows), seek to obtain more than one credit rating. Panel C of Table 2 shows that 57 out of the 313 rated firms possess a first credit rating at the cut-off point (i.e. between BB and BBB). Of these, 26 companies were assigned a marginal non-investment grade and the other 31 received a grade in the investment band. Further, 47 out of the 57 firms (or 83%) sought a second credit rating. In contrast, of the remaining 256 out of 313 rated firms that did not receive the first rating at the investment-grade cut-off, only 97 obtained an additional rating (or 38%). This suggests that companies at the investment-grade cut-off are more likely to seek a second credit rating to improve their creditworthiness. Panel D shows that ten firms with a BB or BB+ as their first credit rating received a follow-up non-investment grade from the second CRA. In contrast, all but two of the 33 IPOs with a marginal investment grade (BBB- and BBB) achieved an equal or higher credit rating from the second CRA (a non-investment grade was issued in the other two cases).

To sum up, Table 2 suggests that the characteristics of unrated IPOs are very different from those with a single rating or multiple ratings. In contrast, while there are differences between the latter two types of IPOs, they are smaller than the differences we observe between unrated IPOs and rated IPOs.

To sum up, multi-rated IPO firms are the largest and oldest firms in the sample. On average, they also exhibit the highest levels of auditor reputation. Firms with these characteristics are intrinsically less affected by information asymmetry as a substantial amount of information about them is already available to investors, which lowers the perceived risk associated with the offering. Hence, in the analysis that follows, we compare multi-rated IPOs with single-rated IPOs.

4.3. Methodology

To study the impact of credit ratings on IPO underpricing, we specify the following treatment effects model:

$$Y_i = \alpha + \beta X_i + \gamma CR_i + \varepsilon_i \quad (1)$$

where Y_i is the level of IPO underpricing (or the magnitude of the filing price revision), X_i is a $1xK$ vector of exogenous explanatory variables that reflect the IPO characteristics, and β is a $Kx1$ vector of coefficients; CR_i enters the equation as an indicator variable that is equal to one if the firm secures at least one rating, and zero otherwise. Of interest is the coefficient γ because it predicts the mean treatment effect of having multiple credit ratings on IPO pricing. Finally, ε_i is an independently and identically distributed (i.i.d.) random variable.

We conduct our analysis using multivariate ordinary least squares (OLS) regressions. For the coefficients to be unbiased, the γ coefficient needs to be free from feedback effects and thus uncorrelated with ε_i (i.e. $Cov(CR_i,\varepsilon_i) = 0$). However, the acquisition of multiple credit ratings is unlikely to be exogenous. Indeed, it is plausible to assume that an IPO company will seek multiple credit ratings if the benefits, i.e. the expectation of superior first trading day performance, outweigh the costs of the extra rating. In this case, endogeneity and self-selection bias could lead to incorrect inferences.

Heckman (1979) argues that selection bias could compromise the robustness of the OLS estimates, bringing the omitted variables problem to the surface. To address this, he proposes a two-stage procedure. The first stage consists of estimating a probit regression, that is, the selection equation, and thus obtaining the estimates of ω in Equation 2 (see below), which in our case estimates the probability of a firm having at least two credit ratings. Specifically, we model this selection equation as follows:

$$CR_i^* = \omega W_i + \mu_i \quad (2)$$

$$\text{where: } CR_i = \begin{cases} 1, \text{ if } CR_i^* > 1 \\ 0, \; if \; CR_i^* = 1 \end{cases}$$

In Equation 2, CR_i^* is a latent variable, W_i is a set of quantifiable determinants of CR_i, ω is a vector of coefficients to be estimated (denoted by ω' in Equation 3 below), and μ_i is the residual term. Unobservable determinants of W_i that could potentially affect the credit rating acquisition process, such as R&D plans, are incorporated in Equations 1 and 2 through ε_i and μ_i, respectively. A correlation between the two error terms confirms the existence of endogenous selection.

Following An and Chan (2008), we correct for self-selection bias via the following augmented equation:

$$E[Y \mid CR = 1] = \beta' X + \gamma + E[\varepsilon \mid CR = 1] = \beta' X + \gamma + \rho\, \sigma_\varepsilon \frac{\varphi(\omega' W)}{\Phi(\omega' W)} \quad (3)$$

Similarly, the equation for single-rated IPOs is:

$$E[Y \mid CR = 0] = \beta' X + \rho\, \sigma_\varepsilon \frac{-\varphi(\omega' W)}{1 - \Phi(\omega' W)} \quad (4)$$

By subtracting Equation 4 from Equation 3, we derive the expected impact of two or more credit ratings on the level of initial returns:

$$E[Y \mid CR = 1] - E[Y \mid CR = 0] = \gamma + \rho\, \sigma_\varepsilon \frac{\varphi(\omega' W)}{\Phi(\omega' W)(1 - \Phi(\omega' W))} \quad (5)$$

where φ and Φ represent, respectively, the distribution function of the standard normal distribution and its cumulative distribution function.

Econometrically, Equation 5 provides both the sign and scale of the effect of multiple credit ratings on IPO pricing. This effect is given via the coefficient γ, which corresponds to the OLS estimate from Equation 1. However, now the bias can be eliminated via the addition of the Inverse Mills ratio (λ), which was missing from the initial multivariate regression analysis. The correction term conditional on the existence of multiple credit ratings takes the following form:

$$\lambda = \frac{\varphi(\omega' W)}{\Phi(\omega' W)} \text{ if CR=1 or } \lambda = \frac{-\varphi(\omega' W)}{1 - \Phi(\omega' W)} \text{ if CR=0} \quad (6)$$

To verify the robustness of our estimates, we also employ two-stage least-squares (2SLS) in the spirit of Heckman (1979). Under this approach, we must no longer assume normality in the distribution of the residuals. Essentially, in the 2SLS procedure the first-step equation is a probit regression of the endogenous variable on the vector of all the available instruments that constitute W_i. In the second stage, Equation 1 is estimated under OLS, while the dichotomous regressor CR_i is replaced by the fitted probabilities we obtained from the reduced form. The use of predicted values is crucial for our analysis. As the extant literature does not specifically prescribe a set of parameters that should be included in Equation 2, this technique provides a degree of flexibility for the choice of explanatory variables. The reason that we extend our chosen variables beyond those reported in the literature is to eliminate the impact of omitted variables on our results. In addition to the Heckman model, we use maximum likelihood estimation (MLE) to calculate the selection and outcome equations concurrently. The MLE approach might prove more efficient than the Heckman model if the residuals ε_i and μ_i, in Equations 1 and 2, follow a bivariate normal distribution.

4.4. Instrumental Variables

The instruments that we use in our empirical analysis are the proportion of other firms in the same industry[9] that have multiple ratings (*Industry Ratings*) as well as the percentage of firms in the industry that went bankrupt (*Bankruptcy*). Our instruments are motivated as follows: (i) If industry peers are more likely to have multiple ratings, then there should be pressure on single-rated firms to obtain a second rating for their IPO. (ii) A hike in bankruptcies should push single-rated firms to apply for a second rating to show that they are not at risk. Hence, we utilize the following two variables: *Industry Ratings* and *Bankruptcy*. Our approach follows a similar methodology as in the extant literature (e.g. Chemmanur et al., 2018; Coles et al., 2017).

Initially, we run probit regressions to estimate the probability of a company having multiple credit ratings. In the second-stage regression, we regress the level of IPO underpricing on the predicted value of the probability of multiple credit ratings (*Predicted (Rating)*) retrieved from the first-stage estimation as well as a group of control variables.

The first- and second-stage regressions of the proposed instrumental variable (IV) procedure are as below:

$$Prob(Multiple\_Credit\_Ratings = 1)_{it} = a_0 + a_1(Instrument)_{it} + a_3 X_{it} + \varepsilon_{it} \tag{7}$$

$$IPO\ Underpricing_{it} = \beta_0 + \beta_1 Predicted(Multiple\_Credit\_Ratings)_{it} + \beta_2 Z_{it} + \varepsilon_{it} \tag{8}$$

In the first-stage regression model of the 2SLS approach (Equation 7), we regress the probability of the existence of multiple credit ratings on the instruments, either the *Industry Ratings* or *Bankruptcy*,

[9] We use the two-digit Standard Industry Classification (SIC) codes to categorize firms into the same industry.

and another six independent (control) variables X_{it} namely, *Industry Fraction*, *Profit*, *Tangibility*, *Log Sales*, *Growth*, *Aged*, *Leverage* and *CRL cut-off* (see Appendix A for the definitions of these variables).

In the second-stage regression of the 2SLS approach (Equation 8) we regress the level of IPO underpricing (or the filing price revision as a robustness check) on the predicted value of the probability of the existence of multiple credit ratings retrieved from the first-stage estimation, as well as on a group of control variables Z_{it}, namely *Overhang*, *Underwriter*, *Auditor Reputation*, *Primary Shares*, *Revisions*, *LogAge*, *Timelag*, *Internet Firm* and *Dotcom Period*. The results of the first and second-stage regression are reported in Specification 1 in Panel A and B of Table 3.

Our findings from Specification 1 in Panel A and B of Table 3 indicate that the instruments *Industry Ratings* and *Bankruptcy* are linked to the probability of multiple credit ratings (Panel B is similar to Panel A but uses *Bankruptcy* instead of *Industry Ratings* as an instrument). Notably, the coefficient on the instrument in the first-stage regression is significant and positive at the 1% level. Further, the value of the F-statistic for the first-stage regression (i.e., 25.03 and 35.53 for Specification 1 in Panel A and B respectively) exceeds the critical value of 10. Our projections show that the higher the percentages of firms in the industry (i) with multiple ratings and (ii) that went bankrupt, the higher the probability for the firm to obtain multiple credit ratings. In addition, the second-stage regression indicates a negative and highly statistically significant (at the 1% level) link between *Predicted (Rating)* and the level of underpricing. In other words, multiple ratings reduce underpricing more than a single rating. This finding corroborates our Hypothesis 1.

5. Empirical Analysis

5.1. Multiple Credit Ratings and Initial Returns

In this section, we explain the first trading day performance of multi-rated companies as compared to single-rated companies. Our first hypothesis suggests that firms with multiple credit ratings have better IPO performance than those with a single rating. To test the validity of this hypothesis, we employ the indicator variable *{2} or {3} Ratings*, which is set to one for those firms that go public with two or three credit ratings, and zero otherwise. The aforementioned variable is regressed on the level of initial returns while the set of control parameters remains broadly unchanged.

Panel A of Table 3 displays the regression results for the OLS specification (Specification 1), the 2SLS specification (Specification 2), the Heckman two-stage procedure (Specification 3), and the MLE two-equation treatment model (Specification 4). The instrument in the latter three specifications is

Industry Ratings. Panel B is similar to Panel A but uses *Bankruptcy* instead of *Industry Ratings* as an instrument.

Using the 313 rated firms[10], we find for both Panel A and Panel B of Table 3 that the key binary variable is always highly significant (at the 1% level) and always negative across all estimation techniques. In support of Hypothesis 1, our OLS specification suggests that IPOs with multiple credit ratings have about 5.69 percentage points less underpricing than companies with one rating (see Specification 1 of Panel A). Economically, this translates into an average increase in proceeds of $24.68 million[11]. These results support Hypothesis 1.

Next, our findings provide further insights into the determinants of IPO underpricing. We observe a positive and highly significant coefficient on *Overhang*: Dilution costs are lower for issues with greater overhang, resulting in greater underpricing. Corroborating Beatty and Welch (1996), Loughran and Ritter (2004), and An and Chan (2008), we report that IPOs underwritten by top-tier underwriters are underpriced more. The positive sign for *Revisions* is in line with the "partial adjustment" phenomenon (see Hanley, 1993). *Timelag* has a negative sign, suggesting surprisingly that the longer the period between the last day of the stock's public offering and the first day of its listing, the lower is the underpricing. Finally, *Internet Firms*, as per Ljungqvist and Wilhelm (2003), as well as the period after the dotcom crisis are positively related with returns to investors. This is to be expected because these companies are characterized by greater uncertainty and an increased asymmetry of information between issuers and underwriters.

From Panel B of Table 2 we know that IPOs with multiple credit ratings are more likely to appoint reputable underwriters or auditors than those with a single rating. Hence, how do these two endogenous choices by the IPO firm of seeking credit ratings and reputable underwriters or auditors interact? Panel C of Table 3 shows the interactions between the indicator for multiple ratings on the one side and underwriter or auditor reputation on the other side, using OLS. The parameter estimates indicate that firms with multiple ratings as well as those with underwriters or auditors of the highest rank have substantially lower underpricing than firms with a single rating. Importantly, after adjusting for these interactions, we still find that our key result holds.

[10] As a robustness check, we also run our models with the full sample of 4,251 IPOs. The findings are qualitatively the same.
[11] The average for the IPO proceeds (for firms with at least one credit rating) is $433.87 million.

5.2. Effects of Credit Rating Levels

The empirical evidence presented so far confirms Hypothesis 1 on the lower underpricing of IPOs with multiple credit ratings compared to those with just one rating. To test the validity of Hypothesis 2, we examine whether there is a negative effect from a higher credit rating level on underpricing when the firm has more than one credit rating. To achieve this, we utilize the variables *CRL {2 and 3 Ratings}* and *CRL {1 Rating}*. The former variable represents the average credit rating level of a multi-rated firm, and the latter the credit rating level of a single-rated firm.

Table 4 suggests that our results are robust across the OLS (Specification 1), the 2SLS approach (Specification 2), as well as the Heckman two-stage procedure (Specification 3)[12]. The results suggest that credit rating levels matter only for IPOs with more than one rating. In economic terms and focusing on the OLS estimation, this means that if the credit rating level for multi-rated companies increases by one notch above the average, the level of initial underpricing decreases by 17.06%. Alternatively, this corresponds to an average increase in IPO proceeds of approximately $74.01 million. Similarly, Kisgen and Strahan (2010) find that a one-notch higher rating corresponds to a 39-basis-point reduction in the firm's cost of debt. To summarize, these results support Hypothesis 2.

Further, we assess the impact of *Credit Rating Dispersion* on IPO underpricing by computing the difference between each firm's second and first rating. Following Fracassi et al. (2016), we consider the rating dispersion as a measure of credit analyst optimism or pessimism (see also Kisgen et al., 2020). In particular, optimism (pessimism) corresponds to firms with a stronger (weaker) second rating. As per our expectations, we find a negative (positive) and highly significant association (at the 1% level) between credit analyst optimism (pessimism) and underpricing.

5.3. Multiple Credit Ratings and IPO Price Revision

In this subsection, we test the validity of Hypothesis 3 by studying the link between multiple credit ratings and the magnitude of the IPO price revision (*Revisions*) during the bookbuilding process for the sample of rated firms. The dependent variable is the difference between the offer price and the midpoint of the

[12] While MLE and the Heckman two-stage estimation techniques typically arrive at the same results, in the case of Table 4 the MLE runs into computational difficulties and thus the MLE regression outcome is not tabulated.

initial filing price range, divided by the offer price. The key independent variable is the indicator variable *{2} or {3} Ratings*[13].

Similar to Table 3, Panel A of Table 5 displays the regression results for the OLS specification (Specification 1), the Heckman two-stage procedure (Specification 2), the MLE two-equation treatment model (Specification 3), and the 2SLS approach (Specification 4) where the instrument is *Industry Ratings*. Panel B[14] is similar to Panel A but uses *Bankruptcy* instead of *Industry Ratings* as an instrument.

Importantly, Panel A and Panel B of Table 5 show that the estimated key indicator coefficient displays the expected negative sign. This is the case across all estimation techniques. This outcome supports Hypothesis 3, which states that multiple credit ratings decrease the magnitude of the filing price revision more than a single credit rating.

5.4. Investment Grade and IPO Pricing

In this subsection, we focus on companies with investment-grade ratings because speculative-grade ratings are unlikely to act as a positive signal of firm quality. In line with our argument, Ederington and Goh (1998), Blanco et al. (2005), and Jorion et al. (2005) report systematically larger abnormal returns for investment-grade firms than for those with speculative ratings. Following Helwege and Turner (1999), we initially construct an indicator variable taking the value of one for firms with (single or multiple) credit ratings of at least BBB- from S&P and Fitch or Baa3 from Moody's, and zero otherwise.

Table 6 reports the coefficients that measure the effect of *Investment Grade* on the level of IPO pricing. The OLS estimation technique employed in Specification 1 generates a significant (at the 5% level) coefficient on *Investment Grade*, and with the hypothesized negative sign. Previous evidence from An and Chan (2008), based on S&P ratings only, does not suggest a relationship between an investment-grade rating and IPO underpricing. Our findings indicate a strongly negative association between investment-grade ratings and IPO underpricing. In other words, we find that firms with an investment-grade rating are associated with substantially lower IPO underpricing[15]. Economically, this translates into an average increase in IPO proceeds of approximately $20.92 million.

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[13] This indicator variable takes a value of one if the firm has multiple credit ratings, and zero otherwise.

[14] As a robustness check we re-estimate Specifications 2 and 3 of Panel A of Table 5 by replacing the variable *Industry Ratings* with *Bankruptcy* (see Panel B of Table 5). The findings are qualitatively the same.

[15] The Heckman and MLE estimation techniques did not return very strong outcomes and thus these regressions were omitted from the table.

Given the negative results of An and Chan (2008), it might be the case that our positive results are driven by the multi-rated IPOs. To check whether this is indeed the case, we generate two new indicator variables, namely *Investment Grade {1 Rating}* and *Investment Grade {2 and 3 Ratings}*. The former takes the value of one for firms with an investment-grade rating and this rating being the only credit rating, and zero otherwise. The latter takes the value of one if the firm received ratings from two or more CRAs with at least one of the ratings at investment grade, and zero otherwise. Specification 2 in Table 6 suggests that an investment-grade rating for companies with only one credit rating has no impact on the level of IPO pricing (similar to An and Chan, 2008). However, firms with at least two credit ratings, including at least one at the investment grade, leave significantly less money on the table. In terms of economic significance, this corresponds to an average increase in proceeds of approximately $29.33 million. Thus, we provide additional evidence that an investment-grade rating does matter for multi-rated companies. These results qualify our findings obtained from Specification 1 of Table 6.

6. The Impact of Multiple Credit Ratings on IPO Firm Survivorship

To test the validity of Hypothesis 4, we estimate a hazard model (see Appendix B for more details on the methodology). Panel A of Table 7 provides the distribution of IPOs across the different types of survival status (i.e. failed, acquired, or surviving) until December 2016 as well as for the five years after going public (see also Figures 1 and 2). Companies with multiple credit ratings experienced lower failure (higher survival) rates than companies with a single rating. In particular, up until 2016, approximately 12% of multi-rated companies failed, whereas companies with a single rating experienced a significantly higher failure rate of 15%. Correspondingly, in the same period, 49% of multi-rated firms survived, whereas companies with a single rating experienced a lower survival rate of 46%. Similar patterns are observed for the five years after going public[16].

The Kaplan-Meier and Nelson-Aalen curves in Figures 1 and 2 provide further insights. In Figure 1, the survival function two years after the IPO for companies with multiple ratings lies above the equivalent function for firms with a single rating. Over time, this gap widens. In particular, the probability of a multi-rated firm surviving two years after the IPO is close to 100%, while that of a firm with a single rating is substantially lower, at approximately 89%. This gap between multi-rated companies and single-

[16] The years with the highest number of failures and survivals are 2002 and 2015, respectively. The Scientific Instruments sector has the highest failure rate (33%) while the Computer Equipment and Services sector has the highest survival rate, at almost 62%. Because of space limitations, these results are not tabulated but are available upon request.

rated companies persists five years after the IPO, with a survival rate of about 88% for multi-rated companies and 80% for single-rated ones.

Figure 2 plots the hazard curves for the failed, acquired, and surviving IPOs. The findings corroborate the results from the Kaplan-Meier estimator. Two years after the IPO, the curve for the multi-rated IPOs is below that for the IPOs with a single rating, while the vertical distance between the two curves increases substantially over time. More specifically, two years after going public, multi-rated and single-rated firms have a likelihood of failure of approximately 1% and 9-10%, respectively. These results support Hypothesis 4 that firms with multiple ratings are more likely to survive.

Our parameter estimates for the Cox proportional hazard model on the probability of failure and time-to-failure of IPO firms with multiple ratings, controlling for various IPO characteristics and instruments that have an impact on survival, are reported in Panel B of Table 7. In Specification 1, the main coefficient of interest is that of *{2} or {3} Ratings*, which is negative and statistically significant at the 5% level. This result indicates that IPO companies with multiple ratings have a lower probability of failure and hence a longer survival time in comparison to IPO companies with just one rating. This result corroborates the results obtained from the non-parametric analysis above and provides further support for Hypothesis 4. In Specification 2, we report the hazard ratio for each of the independent variables. For the multi-rated companies, the hazard ratio is 0.44, which suggests that the risk of failure for these firms is only 44% of the risk of failure for companies with a single rating.

Further, we introduce a new control variable, *Borrowing Cost*, which serves as a proxy for the firm's cost of borrowing (measured as the ratio of the interest expense to earnings before interest, taxes, depreciation, and amortization (EBITDA)) and relates to CRAs' role of evaluating the ability of companies to pay back their debt (Ivashina and Scharfstein, 2010). The coefficient on this variable is significant and positive at the 5% level. This means that if the company's cost of borrowing increases, its risk of failure will increase and hence its survival time will shorten. The hazard ratio of the borrowing cost is 1.06, indicating that for each increase in the borrowing cost by one standard deviation, the company's failure rate rises by 6 percentage points.

To sum up, we find consistent support for Hypothesis 4 that multi-rated IPOs have a greater chance of survival than single-rated ones.

7. Robustness Checks

Thus far, our results indicate that firms with multiple ratings experience lower levels of underpricing (as well as smaller filing price revisions) than firms with a single rating. In this section, we conduct two identification tests to assess causality as well as several tests to confirm the robustness of our findings.

7.1. Propensity Score Matching

To account for potential endogeneity, we employ propensity score matching with the maximum caliper set to 0.01 and nearest neighbor matching (set to 1). In the first step, we estimate the propensity score, which is the conditional probability of receiving treatment (having multiple ratings rather than a single rating) given a firm's pre-treatment characteristics, via a probit regression. We include *Filing Price Revisions* as well as various IPO characteristics in the probit regression, that is, *Overhang*, *Underwriter Reputation*, *Auditor Reputation*, *Primary Shares*, *Log Proceeds (Size)*, *Log Age*, *Timelag*, *Internet Firm*, and *CRL cut-off*.

Table 8 presents the results for the average treatment effect of the treated (ATET) for IPO firms with multiple ratings compared to those with a single credit rating. The results support Hypothesis 1. The magnitude of the estimate is also economically meaningful, suggesting that multiple ratings reduce underpricing (more than the single ratings do) by 6.72%. This translates into an average increase in proceeds of $29.15 million.

7.2. Instrumental Variable Analysis

To explore further the robustness of our results (i.e. multiple ratings reducing IPO underpricing more than single ratings) we utilized alternative instruments, i.e. the median as well as the mean of the credit rating level of the industry for each year. In addition, we employed the Dodd-Frank Act and industry leverage. The findings corroborate our results (the latter are not tabulated).

7.3. Further Robustness Tests

Following the previous literature, we conduct additional robustness tests (not tabulated) that include (1) measuring the initial returns up to the end of the eleventh day of trading and for the first trading month (see Chambers and Dimson, 2009); (2) eliminating all IPOs in industries with a Standard Industrial

Classification (SIC) code of 6 (Lowry and Shu, 2002); and (3) censoring underpricing at the 1^{st} and 99^{th} percentiles, and alternatively at the 5^{th} and 95^{th} percentiles, to account for outliers.

8. Conclusion

This paper provides novel evidence of the impact of multiple credit ratings on IPOs. We find strong and consistent evidence that multiple credit ratings reduce IPO underpricing more than single ratings.

Our study contributes to the extant literature, in particular, An and Chan (2008), Bruno et al. (2016), Hilscher and Wilson (2017), Sangiorgi and Spatt (2017a), Behr et al. (2018), and Flynn and Ghent (2018). In contrast to An and Chan (2008), who focus on S&P credit ratings, our study considers multiple credit ratings by the three main CRAs, i.e. S&P, Moody's, and Fitch. The most popular CRA for IPOs is S&P, followed by Moody's, and then Fitch. Comparing the three CRAs, we document that Moody's rarely awarded a higher rating than S&P, while for approximately 45% of the IPOs S&P and Moody's awarded the same rating.

Our findings are as follows. First, multiple credit ratings reduce both IPO underpricing and the magnitude of the filing price revision. Second, while we confirm the finding of An and Chan (2008) that the level of a single credit rating does typically not affect IPO underpricing, the (average) level does matter when the issuing firm has more than one credit rating. Third, firms with one credit rating on the borderline between investment and non-investment grades (namely BB- and BBB+) are more likely to have multiple ratings. This suggests that such firms request a second credit rating to further certify their quality or to attempt to cross the cut-off point. Our results suggest that firms just below the investment grade do not receive an upgrade to the investment grade following the acquisition of a second rating. On the contrary, they obtain a second rating that is either equal to or lower than the previously acquired one. Fourth, our findings highlight that multi-rated firms with at least one rating at the investment grade benefit from significantly reduced levels of IPO underpricing, whereas we find no such evidence for firms with just one rating at investment grade. Finally, firms with multiple credit ratings have a greater chance of survival than firms with only one rating. This result indicates that the beneficial impact of multiple credit ratings on IPO underpricing is a reflection of the greater magnitude of the uncertainty-reducing effect of credit ratings.

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Appendix A: Variable Definitions

Panel A: Measures of IPO Pricing	
Filing Price Revisions (Revisions)	The difference between the offer price and the midpoint of the initial filing price range, divided by the offer price.
Investor Valuation	The percentage difference between the offer price and the book value of equity as reported in the IPO prospectus, divided by the offer price.
Tobin's Q	The sum of total equity, (net) current liabilities and the book value of outstanding long-term debt, divided by the book value of total assets.
Underpricing (Initial Return)	The percentage difference between the first-day closing price from the Center for Research in Security Prices (CRSP) and the offer price as reported in the S-1 form.

Panel B: Credit Rating Related Variables	
Rating	Indicator variable that equals 1 if the firm has a single or multiple credit ratings from any of the three largest CRAs (Standard & Poor's, Moody's and Fitch), and 0 otherwise.
Credit Rating Levels (CRL)	Level of rating prior to the IPO event. A value of 22 is assigned for AAA ratings, 21 for the next lowest grade (AA) and so on until we reach the lowest grade (D) which takes a value of 1.
CRL {1 Rating}	Credit rating level for companies with one credit rating from either Standard & Poor's, Moody's or Fitch.
CRL {2 and 3 Ratings}	Mean credit rating level for companies with multiple credit ratings.
CRL cut-off	Binary indicator that equals 1 for companies that received a rating between BB and BBB, and 0 otherwise.
Investment Grade	Binary indicator that equals 1 for companies with investment-grade ratings, and 0 otherwise.
Investment Grade {1 Rating}	Binary indicator that equals 1 for single-rated firms that acquired an investment-grade rating, and 0 otherwise.
Investment Grade {2 or 3 Ratings}	Binary indicator that equals 1 for multi-rated firms that obtained at least one credit rating at investment-grade level, and 0 otherwise.
{2} or {3} Ratings	Binary indicator that equals 1 for firms that secure multiple credit ratings (either 2 or 3) from the three largest CRAs (Standard & Poor's, Moody's and Fitch).
{1} Rating	Binary indicator that equals 1 for firms that secure just a single credit rating from either Standard & Poor's, Moody's or Fitch.
Credit Rating Dispersion	The difference between each firm's second and first credit rating level.

	Panel C: IPO Characteristics
Auditor Reputation	Binary indicator that equals 1 for the existence of a reputable auditor, and 0 otherwise. Reputable auditors are considered to be the Big Four, namely PwC, Deloitte and Touche, Ernst and Young, and KPMG.
Log Proceeds	The logarithm of the total amount of proceeds raised during the IPO.
Internet Firm	Binary variable that equals 1 if the firm is in the internet industry (companies with a 2-digit SIC code of 48) and 0 otherwise.
Log Age	The logarithm of the number of years elapsed since the company's foundation at the time of the year of IPO. Dates are obtained from the Field-Ritter database, available at https://site.warrington.ufl.edu/ritter/ipo-data.
Overhang	The ratio of the shares that pre-IPO shareholders retain to the number of new shares issued in the offering.
Primary Shares	Binary indicator that equals 1 if the offering is exclusively primary, and 0 otherwise.
Sales (Log Sales)	The logarithm of net sales in the pre-IPO year, to proxy firm size.
Technology IPO	Binary variable that equals 1 if the IPO is for a company in the technology industry, and 0 otherwise.
Underwriter	Binary indicator that equals 1 for new listings with underwriters of the highest prestige ranking, following Loughran and Ritter (2004), and 0 otherwise.
Venture Capital	Binary indicator that equals 1 for firms with venture-capital backing, and 0 otherwise.
Cost of Borrowing	The ratio of interest expense to earnings before interest, taxes, depreciation and amortization (EBITDA).

	Panel D: List of Employed Instruments and Control Variables
Aged	Binary indicator that equals 1 if the company was at least five years old on the day of the IPO, and 0 otherwise.
Bankruptcy	The percentage of firms in the same industry (using the 2-digit SIC code) that went bankrupt.
Growth	Research and development expenditures divided by net sales.
Industry Fraction (Indfrac)	The logarithm of 1 + the fraction of firms in the same industry (using the 2-digit SIC code) with credit ratings.
Industry Ratings	The proportion of other firms in the same industry (using the 2-digit SIC code) that have multiple ratings.
Leverage	The ratio of total debt to total assets in the pre-IPO year.
Profit	Earnings before interest, taxes, depreciation and amortization (EBITDA) divided by total assets.
Shares (Log Shares)	The logarithm of the total number of shares issued.

Tangibility	Property, plant and equipment divided by total assets.
Timelag	The period between the last date of the stocks' public offering and the first day of their listing.
	Panel E: Crisis Indicator Variables
Dotcom Period	Binary indicator that equals 1 for IPOs during the dotcom bubble, and 0 otherwise.
2008-2009	Binary indicator that equals 1 for IPOs during the financial crisis of 2008-2009, and 0 otherwise

Appendix B: Processes of Analysis

A. Survival Analysis Process

Survival analysis is an econometric technique that has been utilized extensively in previous literature on the determinants of IPO survival (e.g. Jain and Kini, 2000; Fama and French, 2004; Espenlaub et al., 2012; Gerakos et al., 2013; Alhadad et al., 2014). Its key advantage over alternative techniques, such as a cross-sectional logistic model, lies in its ability to account for both occurrence and time-to-event. Furthermore, survival analysis is able to examine both censored and time-series data over different horizons (LeClere, 2000; Shumway, 2001). Indeed, the time window varies for each of the firms in our sample given the different IPO dates. In particular, IPO firms are tracked until the end of 2016. Hence, a firm with an IPO early in the year 2000 is tracked over 17 years, whereas a firm that went public in 2012 is tracked for just five years.

In order to analyse the link between multiple ratings and IPO survival, we employ both non-parametric and semi-parametric estimation techniques. The non-parametric ones allow us to examine and compare the survival rates as well as the failure risks of multi-rated IPOs with those with just one credit rating. Thereby, we are able to determine whether or not multiple ratings benefit firm survival.

The survival function projects the probability that a firm survives up to a specific time. For example, if multiple ratings increase the survival rate of the issuing firm, then the curve of the survival function for multi-rated companies will be above the curve of firms with just one rating. To facilitate this we estimate the survival functions for both groups of firms via the Kaplan–Meier estimator, which is as follows:

$$\hat{S}(t) = \prod_{t_i \leq t} \frac{n_i - d_i}{n_i} \tag{10}$$

where d_i denotes the number of failed companies at time t_i, and n_i is the number of firms at risk at time t_i. Finally, we use the log-rank test to assess the difference between the survival functions of multi-rated IPOs and IPOs with just one credit rating.

The estimated hazard function returns the conditional probability of failure given that the enterprise survived up to a specific time period. In our analysis, this means that if multiple ratings diminish the risk of failure, then the hazard function for multi-rated IPOs will be below that of firms with just one rating. Accordingly, we calculate the hazard function for each of the two groups of enterprises using the Nelson-Aalen estimator, which is as follows:

$$\widehat{H}(t) = \sum_{t_i \leq t} \frac{d_i}{n_i} \tag{11}$$

where d_i denotes the number of failed enterprises at time t_i, and n_i is the number of firms at risk at time t_i.

The second way to conduct our survival analysis is the semi-parametric approach and, in particular, the Cox proportional hazard model. The main advantage of this methodology over alternative ones is the fact that we do not need to pre-specify our baseline hazard function and thus the latter can take any functional form. Finally, no assumption is necessary with respect to the distribution of event dates (see Alhadab et al., 2014).

Our estimation process is as follows:

$$h(t) = h_0(t)\exp\left[\beta * \{2 \ or \ 3 \ Ratings\}_{i,t} + \gamma * Controls_{i,t} + Industry \ Dummies + Year \ Dummies\right] \tag{12}$$

where $h_0(t)$ represents the hazard function, and t the time to failure (for instance, the time to the delisting date). The dependent variable $h(t)$ denotes the risk of failure; hence, a negative (positive) coefficient shows that the failure is less (more) likely to occur and that the survival time is longer (shorter). The exponentiated coefficient estimates the hazard ratio for each explanatory variable. For continuous variables, the change in the rate of hazard for a one-unit increase in the independent variable is 100×(hazard ratio - 1), whereas for binary variables, the risk ratio is estimated by taking the fraction of the hazard for those firms that receive the value 1 and those that receive the value 0 (see Alhadab et al., 2014).

Our primary variable of interest is the existence of multiple credit ratings (*{2} or {3} Ratings*). In addition, we control for various IPO characteristics as well as for instruments, that are suggested by prior literature as determinants of IPO survival, and indicator variables. These include *Overhang*, *Underwriter*, *Auditor Reputation*, *Primary Shares*, *Revisions*, *Venture Capital*, *Timelag*, *Internet Firm*, *Technology*, *Dotcom Period*, *Underpricing*, Profit, *Aged*, *Leverage* and *Industry Fraction*.

Table 1: Summary Statistics

The table reports descriptive statistics for the sample of 4,251 U.S. IPOs over the period 1997–2016. Panel A tabulates the distribution across time for rated and unrated IPOs in absolute numbers and percentages of the total sample each year. It also reports the allocation of credit ratings among the three leading CRAs. Panel B reports the allocation of rating levels for all rated IPOs. Panel C displays which CRA was utilized first among the firms with credit ratings from both S&P and Moody's, as well as which CRA was the least generous. Panel D reports the timeline of obtaining a credit rating (CR) and corresponding average level of underpricing.

Panel A: Distribution of Rated and Unrated IPOs Across Time

Year	Total Sample	Single Credit Rating	Multiple Credit Ratings	S&P	Moody's	Fitch	Unrated IPOs
	N	%	%	%	%	%	%
1997	500	2.00	1.20	2.40	0.80	1.40	96.80
1998	311	2.57	1.29	3.86	1.29	0.00	96.14
1999	495	3.03	3.03	4.85	3.64	0.81	93.94
2000	392	4.08	3.32	5.87	3.83	1.28	92.60
2001	88	6.82	4.55	7.95	5.68	2.27	88.64
2002	80	11.25	5.00	12.5	5.00	5.00	83.75
2003	79	7.59	7.59	13.92	5.06	1.27	86.08
2004	234	3.85	4.70	5.98	5.56	1.71	91.45
2005	210	7.62	3.81	10.00	5.24	0.00	88.57
2006	220	3.18	5.91	7.73	6.36	0.91	90.91
2007	271	4.06	2.21	3.69	3.69	1.11	93.73
2008	43	0.00	4.65	4.65	4.65	0.00	95.35
2009	62	4.84	11.29	11.29	14.52	3.23	83.87
2010	165	5.45	4.24	6.67	4.24	4.85	90.30
2011	132	3.79	5.30	7.58	5.30	1.52	90.91
2012	156	3.21	2.56	3.85	2.56	2.56	94.23
2013	231	7.79	3.46	7.79	6.06	1.73	88.31
2014	302	3.97	3.97	6.62	4.97	0.99	92.05
2015	175	1.71	2.86	3.43	3.43	0.57	95.43
2016	105	0.95	1.90	2.86	1.90	0.00	97.14
Total	**4,251**	**3.98**	**3.39**	**5.74**	**3.95**	**1.32**	**92.64**

Table 1 (Continued)

Panel B: Allocation of Credit Rating Levels by the Three Leading U.S. CRAs

Assigned Level	Grade	S&P Rating	N	Moody's Rating	N	Fitch Rating	N
22	Investment Grade	AAA	1	Aaa	1	AAA	0
21		AA+	0	Aa1	0	AA+	0
20		AA	1	Aa2	1	AA	0
19		AA-	0	Aa3	0	AA-	1
18		A+	1	A1	2	A+	1
17		A	0	A2	0	A	2
16		A-	5	A3	2	A-	7
15		BBB+	7	Baa1	2	BBB+	6
14		BBB	9	Baa2	2	BBB	4
13		BBB-	12	Baa3	4	BBB-	3
12	Speculative Grade	BB+	5	Ba1	1	BB+	7
11		BB	11	Ba2	5	BB	2
10		BB-	35	Ba3	18	BB-	6
9		B+	76	B1	32	B+	2
8		B	46	B2	50	B	2
7		B-	28	B3	30	B-	4
6		CCC+	5	Caa1	12	CCC	4
5		CCC	1	Caa2	5	DDD	5
4		CCC-	1	Caa3	1	DD	0

Panel C: Shopping Sequence for Firms With Ratings by S&P and Moody's

Shopping Sequence	No. of Ratings N	No. of Ratings %	S&P Rating Highest N	S&P Rating Highest %	Moody's Rating Highest N	Moody's Rating Highest %	Same Rating Level N	Same Rating Level %
S&P Rated First	55	43.65	22	40.00	7	12.73	26	47.27
Moody's Rated First	46	36.51	20	43.48	7	15.22	19	41.30
Simultaneous S&P and Moody's Ratings	25	19.84	10	40.00	4	16.00	11	44.00
Total	**126**		**52**	**41.27**	**18**	**14.29**	**56**	**44.44**

Table 1 (Continued)

Panel D: Timeline of Obtaining the First and Second Credit Rating (CR) and Corresponding Average Level of Underpricing		
	Firms, %	**Average Level of Underpricing, %**
CR Within 1 Year Before IPO	62.00	10.31
CR Within 3 Year Before IPO	86.67	11.66
CR Within 5 Year Before IPO	93.33	11.85
Synchronous CRs (within a month)	50.70	8.00
Asynchronous CRs (more than a month)	49.30	10.56

Table 2: Descriptive Statistics for Full Sample, and IPO Firms with No Credit Rating, a Single Rating, and Multiple Ratings

This table provides descriptive statistics for the sample of 4,251 IPOs that were floated on the U.S. stock exchanges between January 1, 1997 and December 31, 2016. All IPOs were extracted from the Securities Data Company (SDC) database, and credit ratings from Bloomberg. Panels A and B report the mean, median, minimum, maximum and standard deviation (s.d.) for IPO pricing and IPO characteristics, respectively, both for the full sample as well as for the IPOs without credit ratings and those with credit ratings (either a single or multiple ratings). Statistical tests for differences in means are also reported. For each variable, the p-value for the test for the difference in means between the two subsamples of firms with a single rating and those with multiple ratings is reported. Panel C reports the number of firms with a first rating from the three CRAs at the borderline between investment and non-investment grade (*CRL cut-off*). There are 57 firms that satisfy the aforementioned condition. Column 1 displays the number and percentage of firms across each CRA with a first rating between BB and BBB. Columns 2 to 5 report the number and percentage of firms across each CRA by non-investment- and investment-grade credit rating level (based on their first rating), respectively. Column 6 tabulates the number of firms that sought a second rating after receiving a first rating at either non-investment or investment grade. Panel D reports the number and percentage of firms with a second rating that was a downgrade, at the same level, or an upgrade, respectively (see Columns 1, 2 and 3), compared to the first rating. In detail, 10 out of the 14 firms that received a first rating at non-investment grade were assigned the same second credit rating, whereas four received a lower one. In contrast, 31 out of the 33 firms with a first rating at investment grade either saw their rating level increase or maintained whereas only two received a second rating at non-investment grade. The definitions of all variables are provided in Appendix A.

Panel A: IPO Pricing

	Full Sample (N = 4251)				**IPOs Without Credit Ratings (N = 3938)**				**IPOs With Single Credit Ratings (N = 169)**				**IPOs With Multiple Credit Ratings (N = 144)**				
	Mean (s.d.)	**Median**	**Min**	**Max**	**Mean (s.d.)**	**Median**	**Min**	**Max**	**Mean (s.d.)**	**Median**	**Min**	**Max**	**Mean (s.d.)**	**Median**	**Min**	**Max**	**Diff. p-value**
Initial Return	22.74 (48.63)	6.67	-97.60	397.60	23.43 (49.64)	6.82	97.60	397.60	15.39 (31.01)	6.74	-21.50	219.20	9.29 (19.81)	5.22	-47.29	122.83	0.00
Filing Price Revision	0.24 (22.70)	0.00	-86.1	717.30	0.38 (23.33)	0.00	-86.10	717.4	-0.25 (11.49)	0.00	-26.66	33.33	-3.17 (12.48)	0.00	-47.06	27.27	0.07
Tobin's Q	4.67 (8.97)	1.16	0.00	75.40	4.97 (9.30)	2.07	0.00	75.4	1.51 (2.90)	0.86	0.00	23.96	1.65 (0.98)	0.79	0.00	7.36	0.00
Investor Valuation	1.31 (1.11)	0.97	-0.90	7.79	1.19 (1.12)	0.96	-0.90	7.73	1.02 (0.87)	0.96	-0.13	2.94	1.44 (1.20)	0.94	-0.01	7.79	0.00

Table 2 (Continued)

Panel B: IPO Characteristics

	Full Sample (N = 4251)				IPOs Without Credit Ratings (N = 3938)				IPOs With Single Credit Ratings (N = 169)				IPOs With Multiple Credit Ratings (N = 144)				
	Mean (s.d.)	**Median**	**Min**	**Max**	**Mean (s.d.)**	**Median**	**Min**	**Max**	**Mean (s.d.)**	**Median**	**Min**	**Max**	**Mean (s.d.)**	**Median**	**Min**	**Max**	**Diff. p-value**
Proceeds	176.50	78.00	4.00	4600.00	140.94	73.50	4.00	4133.33	346.04	190.00	8.25	4600.00	363.10	206.50	11.40	3010.00	0.00
	(295.81)				(247.62)				(558.32)				(501.70)				
Sales	507.32	65.25	0.22	29234.00	408.93	56.24	0.22	29234.00	1315.76	375.53	1.16	26420.00	1755.00	504.45	0.00	24788.00	0.46
	(1875.54)				(1659.14)				(2908.73)				(3510.00)				
Firm Age	18.24	8.00	1.00	224.00	16.77	8.00	1.00	224.00	32.79	21.00	1.00	149.00	38.93	26.00	1.00	165.00	0.00
	(26.44)				(24.95)				(34.08)				(37.29)				
Auditor Reputation	0.73	1.00	0.00	1.00	0.72	1.00	0.00	1.00	0.78	1.00	0.00	1.00	0.85	1.00	0.00	1.00	0.00
	(0.44)				(0.45)				(0.35)				(0.36)				
Underwriter	0.49	0.00	0.00	1.00	0.48	0.00	0.00	1.00	0.72	1.00	0.00	1.00	0.83	1.00	0.00	1.00	0.00
	(0.50)				(0.50)				(0.44)				(0.38)				
Venture Capital	0.50	0.00	0.00	1.00	0.42	0.00	0.00	1.00	0.12	0.00	0.00	1.00	0.06	0.00	0.00	1.00	0.00
	(0.50)				(0.49)				(0.33)				(0.24)				
Primary Shares	0.72	1.00	0.00	1.00	0.73	1.00	0.00	1.00	0.68	1.00	0.00	1.00	0.55	1.00	0.00	1.00	0.00
	(0.45)				(0.45)				(0.47)				(0.50)				
Overhang	5.09	2.80	-0.87	209.97	5.22	2.82	-0.52	209.97	3.86	2.84	-0.87	54.15	3.19	2.36	0.15	15.54	0.00
	(10.20)				(10.53)				(5.55)				(2.62)				
Cost of Borrowing	0.90	0.63	-19.00	1180.35	0.95	0.69	-19.00	1180.35	0.37	0.21	-2.01	14.80	0.24	0.13	-0.78	5.49	0.00
	(27.37)				(28.71)				(1.47)				(0.81)				
Internet Firm	0.09	0.00	0.00	1.00	0.08	0.00	0.00	1.00	0.18	0.00	0.00	1.00	0.02	0.00	0.00	1.00	0.00
	(0.29)				(0.28)				(0.38)				(0.14)				
Dotcom Period	0.20	0.00	0.00	1.00	0.21	0.00	0.00	1.00	0.18	0.00	0.00	1.00	0.19	0.00	0.00	1.00	0.00
	(0.41)				(0.40)				(0.38)				(0.40)				
Credit Rating Dispersion													0.78	1.00	0.00	4.00	-
													(0.84)				

Table 2 (Continued)

Panel C: Firms With Their First Rating Between BB and BBB

	Number of Firms With a First Rating Between BB and BBB (1)		Number of Firms With a First Rating at BB (Non-investment Grade) (2)		Number of Firms With a First Rating at BB+ (Non-investment Grade) (3)		Number of Firms With a First Rating at BBB- (Investment Grade) (4)		Number of Firms With a First Rating at BBB (Investment Grade) (5)		Number of Firms That Sought a Second Rating (6)	
CRA	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
S&P	33	57.89	7	50.00	5	41.67	12	70.59	9	64.29	27	57.45
Moody's	10	17.54	5	35.71	1	8.33	2	11.76	2	14.29	10	21.28
Fitch	14	24.56	2	14.29	6	50.00	3	17.65	3	21.43	10	21.28
Total	**57**	**100.00**	**14**	**100.00**	**12**	**100.00**	**17**	**100.00**	**14**	**100.00**	**47**	**100.00**

Panel D: Number of Firms With a First Rating at Either Non-investment or Investment Grade and a Downgraded, Invariant or Upgraded Second Credit Rating

	Second Credit Rating Downgrade (1)	Second Credit Rating Invariant (2)	Second Credit Rating Upgrade (3)	Total
	N	**N**	**N**	**N**
Firms With a First Rating at Non-investment Grade (BB and BB+)	4	10	0	14
Firms With a First Rating at Investment Grade (BBB- and BBB)	2	18	13	33
Total				**47**

Table 3: Effect of Multiple Credit Ratings on Underpricing

Panel A presents the findings on the effect of multiple credit ratings on the level of initial returns for a sample of 313 U.S. IPOs over the period 1997-2016. Because of missing values, the actual number of observations is below 313. The four econometric techniques are: 2SLS (Specification 1), OLS (Specification 2), the Heckman two-stage procedure (Specification 3) and the MLE two-equation treatment model (Specification 4). In all four specifications, the dependent variable is the level of IPO underpricing, whereas the key independent variable is the predicted value of the probability of multiple credit ratings *Predicted (Rating)* in Specification 1 and the categorical indicator *{2} or {3} Ratings*, that takes the value of 1 if a firm possesses multiple credit ratings prior to the year of IPO, and 0 otherwise for Specifications 2 to 4. *Industry Ratings* is the instrument utilized in the first-stage regression of 2SLS Specification and the selection equation of Heckman and MLE Specifications. Panel B presents the findings on the effect of multiple credit ratings on the level of initial returns for a sample of 313 U.S. IPOs over the period 1997-2016. Because of missing values, the actual number of observations is below 313. The three econometric techniques are: the 2SLS (Specification 1), the Heckman two-stage procedure (Specification 2) and the MLE two-equation treatment model (Specification 3). In all specifications, the dependent variable is the level of IPO underpricing, whereas the key independent variable is the predicted value of the probability of multiple credit ratings *Predicted (Rating)* in Specification 1 and the categorical indicator *{2} or {3} Ratings*, that takes the value of 1 if a firm possesses multiple credit ratings prior to the year of IPO, and 0 otherwise, for Specifications 2 and 3. *Bankruptcy* is the instrument utilized in the first-stage regression of 2SLS Specification and the selection equation of Heckman and MLE Specifications. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects are taken into account in all specifications. Panel C reports the interaction effects between *{2} or {3} Ratings* on the one side and *Underwriter* and *Auditor Reputation* on the other side. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects are taken into account in all specifications.

Panel A

	OLS	2SLS		Heckman		MLE	
		First-stage	Second-stage	Selection	Outcome	Selection	Outcome
VARIABLE	(1)	(2)		(3)		(4)	
{2} or {3} Ratings	-5.69***				-5.31***		-5.62***
	(1.86)				(2.02)		(1.98)
Predicted (Rating)			-24.43***				
			(9.57)				
Overhang	1.99***		0.25***		1.87***		1.86***
	(0.27)		(0.09)		(6.65)		(6.61)
Underwriter	-6.33**		-3.43		-4.92***		-3.98***
	(3.25)		(4.17)		(1.70)		(1.48)
Auditor Rep.	-1.94		0.06		-1.49		-1.46
	(4.21)		(5.20)		(4.44)		(5.52)
Prim. Shares	-0.28		-0.54		-0.77		-0.69
	(3.02)		(3.40)		(3.14)		(4.10)
Revisions	0.68***		0.72***		0.99***		0.99***
	(0.10)		(0.08)		(0.06)		(0.06)
Log Age	0.41		0.38		-0.89		-0.94
	(1.04)		(1.08)		(0.72)		(0.71)
Timelag	-0.02***		-0.01		-0.01		-0.02
	(0.01)		(0.01)		(0.01)		(0.02)
Internet Firm	-1.83		-5.36		-11.01		-10.78
	(9.06)		(11.19)		(9.74)		(8.88)
Dotcom Period	22.41***		21.39***		23.33***		23.68***
	(3.78)		(4.80)		(4.02)		(3.90)
Constant	18.80***		7.33***	-0.35***	-28.68	-2.37***	-26.79
	(5.16)		(2.65)	(0.13)	(30.41)	(0.08)	(17.70)
Industry Ratings		5.22***		5.20***		4.72***	
		(1.78)		(1.62)		(1.28)	
Industry Fraction		1.73**		1.83**		6.69***	
		(0.78)		(0.90)		(0.62)	
Profit		-0.01		0.02		0.02	
		(0.01)		(0.02)		(0.02)	
Tangibility		-0.07		-0.06		-0.05	
		(0.25)		(0.22)		(0.21)	
Log Sales		0.13***		0.10***		0.11***	
		(0.05)		(0.05)		(0.04)	
Growth		-0.01		-0.01		-0.01	
		(0.01)		(0.01)		(0.01)	
Aged		0.16		0.15		0.17	
		(0.32)		(0.30)		(0.28)	
Leverage		-0.09		-0.10		-0.10	
		(0.18)		(0.20)		(0.20)	
CRL cut-off		1.07***		1.10***		1.08***	
		(0.22)		(0.25)		(0.21)	
Inverse Mills Ratio					35.55***		
					(4.56)		
Durbin–Wu–Hausman Test Against H_0: *Variables Are Exogenous (p-value)*		0.01					
Year Fixed Effects	Y	Y	Y	N	N	N	N
Industry Fixed Effects	Y	Y	Y	N	N	N	N
F-Statistic		25.03					
N	289	289	289	289	289	289	289
Adjusted-R^2	0.13	0.10	0.18	-	-	-	-

Table 3 (Continued)

Panel B

	2SLS		Heckman		MLE	
	First-stage	**Second-stage**	**Selection**	**Outcome**	**Selection**	**Outcome**
VARIABLE	(1)		(2)		(3)	
{2} or {3} Ratings				-4.60***		-4.62***
				(1.02)		(1.08)
Predicted (Rating)		13.93***				
		(3.69)				
Overhang		0.28		0.28		0.30
		(0.26)		(0.26)		(0.22)
Underwriter		-3.36*		-5.90**		-5.68**
		(1.87)		(2.78)		(2.60)
Auditor Rep.		-4.01*		-2.85		-2.22
		(2.38)		(4.57)		(4.88)
Prim. Shares		-2.43		-0.31		-0.28
		(1.53)		(3.04)		(3.22)
Revisions		1.07***		1.10***		1.13***
		(0.07)		(0.07)		(0.06)
Log Age		-0.88		-0.90		-0.93
		(0.70)		(0.72)		(0.72)
Timelag		-0.03		-0.01		-0.01
		(0.26)		(0.01)		(0.01)
Internet Firm		-6.35		-8.61		-9.02
		(4.82)		(9.35)		(9.25)
Dotcom Period		27.55***		20.85***		20.70***
		(4.65)		(3.98)		(3.90)
Constant		22.17***	-1.06**	23.49	-2.37***	23.69
		(4.69)	(0.51)	(18.89)	(0.08)	(17.70)
Bankruptcy	9.96***		9.97***		9.90***	
	(2.55)		(2.60)		(2.50)	
Industry Fraction	1.85**		1.88**		5.72***	
	(0.85)		(0.88)		(0.80)	
Profit	-0.01		0.01		0.01	
	(0.01)		(0.01)		(0.01)	
Tangibility	0.15		0.14		0.12	
	(0.32)		(0.30)		(0.28)	
Log Sales	0.11**		0.10**		0.10**	
	(0.06)		(0.07)		(0.08)	
Growth	-0.01		-0.01		-0.01	
	(0.01)		(0.01)		(0.01)	
Aged	0.39		0.40		0.42	
	(0.45)		(0.43)		(0.41)	
Leverage	-0.01		-0.01		-0.01	
	(0.35)		(0.37)		(0.32)	
CRL cut-off	1.05***		1.02***		1.01***	
	(0.23)		(0.20)		(0.21)	
Inverse Mills Ratio				9.42*		
				(5.38)		
Durbin–Wu–Hausman Test Against H_0: *Variables Are Exogenous (p-value)*	0.08					
Year Fixed Effects	Y	Y	N	N	N	N
Industry Fixed Effects	Y	Y	N	N	N	N
F-Statistic	35.53					
N	289	289	289	289	289	289
Adjusted-R^2	0.08	0.10	-	-	-	-

Table 3 (Continued)

Panel C: Interaction Effects Between Ratings and Underwriter or Auditor Reputation

VARIABLE	**OLS** (1)	**OLS** (2)
{2} or {3} Ratings x Underwriter Rep.	-5.36**	
	(2.65)	
{2} or {3} Ratings x Auditor Rep.		-5.30**
		(2.65)
Overhang	2.12***	1.99***
	(0.29)	(0.27)
Underwriter		-6.65**
		(3.53)
Auditor Rep.	-0.75***	
	(3.70)	
Prim. Shares	-1.19	-0.24
	(2.69)	(3.03)
Revisions	0.68***	0.68***
	(0.10)	(0.10)
Log Age	-0.69	-0.42
	(1.13)	(1.03)
Timelag	-0.02**	-0.02**
	(0.01)	(0.01)
Internet Firm	4.73	-1.91
	(8.48)	(9.06)
Dotcom Period	17.73***	22.19***
	(3.42)	(3.75)
Constant	16.22***	16.83***
	(5.65)	(4.07)
Year Fixed Effects	Y	Y
Industry Fixed Effects	Y	Y
N	289	289
Adjusted-R^2	0.26	0.38

Table 4: Effect of Credit Ratings Levels on Underpricing

Panel A reports estimation outputs from four econometric techniques on the effect of single or multiple credit rating levels on the level of initial returns for a sample of 313 U.S. IPOs from 1997 to 2016. Because of missing values, the actual number of observations is below 313. The three estimation techniques are: OLS (Specification 1), the 2SLS approach (Specification 2), and the Heckman two-stage procedure (Specification 3). In Specifications 1 and 2 as well as the outcome regression of Specification 3, the dependent variable is the level of IPO underpricing, while the key independent variables are the credit rating level of single-rated companies (*CRL {1 Rating}*) and the average credit rating level for multi-rated companies (*CRL {2 and 3 Ratings}*). *Industry Rating* is utilized as instrument in Specification 2 and in the selection equation of the Heckman procedure. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% level, respectively. The numbers in parentheses are the standard errors. Industry and year fixed effects are taken into account in all specifications.

	OLS	**2SLS**	**Heckman**	
			Selection	**Outcome**
VARIABLE	(1)	(2)	(3)	
{2} or {3} Ratings				-11.49***
				(3.55)
CRL {1 Rating}	-0.69*	-4.06		-0.68*
	(0.40)	(3.05)		(0.36)
CRL {2 and 3 Ratings}	-0.74***	-3.62***		-0.89***
	(0.28)	(1.22)		(0.25)
Credit Rating Dispersion	-0.68***	-1.17***		-0.75***
	(0.25)	(0.22)		(0.18)
Overhang	2.07***	1.69***		1.88***
	(0.29)	(0.38)		(0.09)
Underwriter	-8.02***	7.93		-8.01***
	(2.98)	(9.75)		(1.65)
Auditor Rep.	0.09	-0.53		0.10
	(3.51)	(7.59)		(2.29)
Prim. Shares	0.33	-12.37		0.27
	(2.49)	(9.06)		(2.55)
Revisions	0.69***	0.71***		0.87***
	(0.10)	(0.14)		(0.06)
Log Age	0.46	-0.21		-0.89
	(1.05)	(1.41)		(0.85)
Timelag	-0.02**	-0.02**		-0.02***
	(0.01)	(0.01)		(0.01)
Internet Firm	3.70	-7.93		3.65
	(7.78)	(2.87)		(2.91)
Dotcom Period	15.05***	23.37***		18.87***
	(3.31)	(7.39)		(3.65)
Technology IPO	-0.31	0.67		-0.27
	(3.10)	(7.31)		(2.02)
Constant	15.87***	39.14**	1.88***	16.53***
	(6.50)	(17.51)	(0.11)	(2.81)
Industry Ratings			5.15***	
			(1.68)	
Industry Fraction			-2.62***	
			(0.82)	
Profit			0.01	
			(0.11)	
Aged			0.32***	
			(0.10)	
Leverage			0.25***	
			(0.10)	
Inverse Mills Ratio				16.24
				(31.72)
Year Fixed Effects	Y	Y	N	N
Industry Fixed Effects	Y	Y	N	N
N	289	289	289	289
Adjusted-R^2	0.38	0.35	-	-

Table 5: Effect of Single and Multiple Credit Rating Acquisitions on Revisions of the Filing Price

Panel A presents the findings on the impact of multiple and single credit ratings on the degree of filing price revision for a sample of 313 U.S. IPOs over the period 1997-2016. Because of missing values, the actual number of observations is below 313. To test the robustness of our results we employ four estimation techniques: OLS (Specification 1), the Heckman two-stage procedure (Specification 2), the MLE two-equation treatment model (Specification 3), and the 2SLS (Specification 4). In all models, the dependent variable is the level of *Filing Price Revisions*. The main independent variable is the binary indicator that take the value of 1 when a firm obtains multiple credit ratings prior to the year of IPO (*{2} or {3} Ratings*), and 0 otherwise. *Industry Ratings* is the instrument in the selection equation of Heckman and MLE as well as Specification 4. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects are taken into account in all specifications.

Panel A

	OLS	**Heckman**		**MLE**		**2SLS**	
		Selection	**Outcome**	**Selection**	**Outcome**	**First-stage**	**Second-stage**
VARIABLE	(1)	(2)		(3)		(4)	
{2} or {3} Ratings	-2.97***		-2.73**		-2.69***		-11.52**
	(1.02)		(1.17)		(1.12)		(5.72)
Overhang	0.46***		0.44***		0.44***		0.22
	(0.15)		(0.16)		(0.19)		(0.32)
Underwriter	-2.01		-1.27		-1.25		2.90
	(1.83)		(1.94)		(1.88)		(4.27)
Auditor Rep.	1.79		2.01		2.01		-0.72
	(2.02)		(2.17)		(2.08)		(3.77)
Prim. Shares	-1.87***		-2.32*		-2.22*		-7.35**
	(0.98)		(1.28)		(1.35)		(3.88)
Log Proceeds	1.54***		1.40**		1.50**		2.14**
	(0.67)		(0.70)		(0.72)		(1.02)
Log Age	-1.47***		-1.54**		-1.49**		-1.03***
	(0.60)		(0.66)		(0.63)		(1.02)
Timelag	-0.01		-0.01		-0.01		-0.01
	(0.01)		(0.01)		(0.01)		(0.01)
Internet Firm	0.05		-0.15		-0.12		-1.79
	(4.46)		(4.89)		(4.78)		(8.16)
Dotcom Period	5.26***		5.33***		5.21***		4.26
	(1.83)		(1.99)		(1.87)		(3.60)
Constant	-26.22**	-0.37**	-45.89***	-0.42***	-48.22***	-0.30**	-26.59
	(12.24)	(0.13)	(17.22)	(0.10)	(18.36)	(0.12)	(22.33)
Industry Ratings		5.17***		5.16***		5.17***	
		(1.56)		(1.55)		(1.58)	
Industry Fraction		2.40**		2.38**		2.41**	
		(1.05)		(1.07)		(1.06)	
Profit		0.06		0.05		0.06	
		(0.05)		(0.04)		(0.05)	
Tangibility		0.13		0.12		0.13	
		(0.22)		(0.21)		(0.22)	
Log Sales		0.16**		0.17**		0.17**	
		(0.08)		(0.07)		(0.07)	
Growth		-0.01		-0.01		-0.01	
		(0.01)		(0.01)		(0.01)	
Aged		0.01		0.12		0.01	
		(0.01)		(0.08)		(0.01)	
Leverage		-0.06		0.18		-0.07	
		(0.16)		(1.02)		(0.16)	
CRL cut-off		1.05***		1.02***		1.06***	
		(0.18)		(0.20)		(0.16)	
Inverse Mills Ratio			41.09**				
			(20.57)				
Durbin–Wu–Hausman Test Against H_0:Variables Are Exogenous (p-value)						0.07	
Year Fixed Effects	Y	N	N	N	N	Y	Y
Industry Fixed Effects	Y	N	N	N	N	Y	Y
F-statistic						45.67	
N	289	289	289	289	289	289	289
Adjusted-R^2	0.08	-	-	-	-	0.07	0.05

Table 5 (Continued)

Panel B presents our findings on the impact of multiple and single credit ratings on the degree of filing price revision for a sample of 313 U.S. IPOs over the period 1997–2016. Because of missing values, the actual number of observations is below 313. To test the robustness of our results we employ two estimation techniques: the Heckman two-stage procedure (Specification 1) and the MLE two-equation treatment model (Specification 2). In all models, the dependent variable is the level of *Filing Price Revisions*. The main independent variable is the binary indicator that take the value of 1 when a firm obtains multiple credit ratings prior to the year of IPO (*{2} or {3} Ratings*), and 0 otherwise. *Bankruptcy* is the instrument in the selection equation of Heckman and MLE. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% level, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects were taken into account in all specifications.

Panel B

	Heckman		**MLE**	
	Selection	**Outcome**	**Selection**	**Outcome**
VARIABLE	(1)		(2)	
{2} or {3} Ratings		-4.18**		-4.16***
		(1.78)		(1.70)
Overhang		2.14***		2.11***
		(0.30)		(0.34)
Underwriter		-6.10*		-6.17
		(3.63)		(3.60)
Auditor Rep.		1.33		1.32
		(4.06)		(4.24)
Prim. Shares		-2.68		-2.70
		(2.88)		(2.80)
Log Proceeds		-1.24		-1.24
		(1.31)		(1.32)
Log Age		-0.35		-0.36
		(1.24)		(1.27)
Timelag		-0.01		-0.01
		(0.01)		(0.01)
Internet Firm		-6.25		6.88
		(9.24)		(10.34)
Dotcom Period		17.17***		18.10***
		(3.73)		(3.06)
Constant	-0.37	24.84	-0.38	25.85
	(0.28)	(32.98)	(0.10)	(35.67)
Bankruptcy	0.59***		0.60***	
	(0.16)		(0.18)	
Industry Fraction	2.40**		2.40**	
	(1.06)		(1.07)	
Profit	0.01		0.01	
	(0.01)		(0.01)	
Aged	-0.01		-0.01	
	(0.01)		(0.01)	
Leverage	-0.06		-0.06	
	(0.16)		(0.15)	
Inverse Mills Ratio		16.78		
		(38.52)		
Year Fixed Effects	N	N	N	N
Industry Fixed Effects	N	N	N	N
N	289	289	289	289
Adjusted-R^2	-	-	-	-

Table 6: Investment Grade and Initial Price Return

The table displays the estimation outputs for the effect of *Investment Grade* on IPO underpricing for a sample of 313 rated U.S. IPOs for 1997-2016. Because of missing values, the actual number of observations is below 313. *Investment Grade* takes the value of 1 if the firm has a credit rating at investment grade, and 0 otherwise. *Investment Grade {1 Rating}* and *Investment Grade {2 and 3 Ratings}* take the value of 1 if the firm has obtained a credit rating at investment grade and possesses a single or multiple ratings, respectively and 0 otherwise. For those companies awarded multiple ratings at both investment and non-investment grade, we take the highest credit rating level received. All other variables are defined in Appendix A. The estimation technique is OLS. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% level, respectively. The numbers in parentheses are the standard errors. Industry and year fixed effects are taken into account in all specifications.

	OLS	**OLS**
VARIABLE	(1)	(2)
Investment Grade	-4.82**	
	(2.25)	
Investment Grade {1 Rating}		-5.98
		(4.01)
Investment Grade {2 and 3 Ratings}		-6.76**
		(2.78)
Overhang	2.05***	2.20***
	(0.27)	(0.30)
Underwriter	-8.36***	-8.36***
	(2.91)	(3.20)
Auditor Rep.	0.04	-1.88
	(3.49)	(3.75)
Prim. Shares	0.54	0.62
	(2.47)	(2.56)
Revisions	0.69***	0.68***
	(0.10)	(0.10)
Log Age	0.44	0.72
	(1.04)	(1.51)
Timelag	-0.02**	-0.02**
	(0.01)	(0.01)
Technology	3.55	3.77
	(7.76)	(7.89)
Dotcom Period	14.71***	15.41***
	(3.19)	(3.53)
Constant	10.07**	11.45*
	(5.15)	(6.90)
Year Fixed Effects	Y	Y
Industry Fixed Effects	Y	Y
N	289	289
Adjusted-R^2	0.39	0.39

Table 7: Distribution of Failed, Acquired, and Surviving IPOs by Issue Year and Industry

Panel A reports the distribution of failed, acquired and surviving IPOs for the full sample from 1997 to 2016 for up to five years after the IPO date. Failed companies are those that are delisted for negative reasons (delisting code 300 or greater). Surviving firms are those that are still active (delisting code equal to 100). Finally, acquired firms are those that are delisted due to acquisition (delisting codes of 200-299). Panel B presents the parameter estimates of the Cox proportional hazard model of failure and the time-to-failure probability for the full sample of 313 U.S. IPOs from 1997 to 2016. The parameter estimates of the model are reported under Specification 1, while the hazard ratios are reported under Specification 2. Because of missing values, the actual number of observations is below 313. The key independent variable is the binary variable *{2} or {3} Ratings*, which is assigned a value of 1 if a firm has multiple credit ratings prior to the year of IPO, and 0 otherwise. Industry and year fixed effects are included, but the coefficients are not reported. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively. The standard errors are reported in parentheses below the coefficient estimates.

Panel A: Distribution of Failed, Acquired, and Surviving IPOs With Multiple and Single Credit Ratings

	From the IPO Date to December 2016				**From the IPO Date to Five Years After Offering**			
	Multiple Credit Ratings		**Single Credit Rating**		**Multiple Credit Ratings**		**Single Credit Rating**	
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Failed	17	12.39	20	15.38	7	6.19	11	8.46
Acquired	46	38.05	50	38.46	23	20.35	29	22.31
Surviving	50	49.56	60	46.15	83	73.45	90	69.23
Total	**113**	**100**	**130**	**100.00**	**113**	**100.00**	**130**	**100.00**

Table 7 (Continued)

Panel B: Cox Proportional Hazard Model

VARIABLE	**Coefficient** (1)	**Hazard Ratio** (2)
{2} or {3} Ratings	-0.81**	0.44
	(0.40)	
Borrowing Cost	0.07**	1.06
	(0.03)	
Overhang	-0.01	0.98
	(0.01)	
Underwriter	-0.65***	0.52
	(0.14)	
Auditor Rep.	-0.59***	0.55
	(0.14)	
Primary Shares	0.14	1.11
	(0.17)	
Revisions	-0.03***	0.98
	(0.01)	
Log Age	-0.32***	0.72
	(0.07)	
Revisions	-0.03***	0.98
	(0.01)	
Venture Capital	-0.11	0.89
	(0.17)	
Timelag	0.01	1.00
	(0.02)	
Internet Firm	0.90***	2.46
	(0.22)	
Technology	0.11	1.12
	(0.18)	
Dotcom Period	0.59***	1.80
	(0.18)	
Underpricing	0.01	1.00
	(0.01)	
Profit	-0.10*	0.90
	(0.06)	
Aged	-0.37**	0.69
	(0.16)	
Leverage	0.18**	1.20
	(0.07)	
Industry Fraction	3.70***	40.58
	(1.22)	
N	195	
Chi-squared	90.34	
Chi-squared Test Probability	0.00	

Figure 1. Kaplan-Meier Survival Estimates

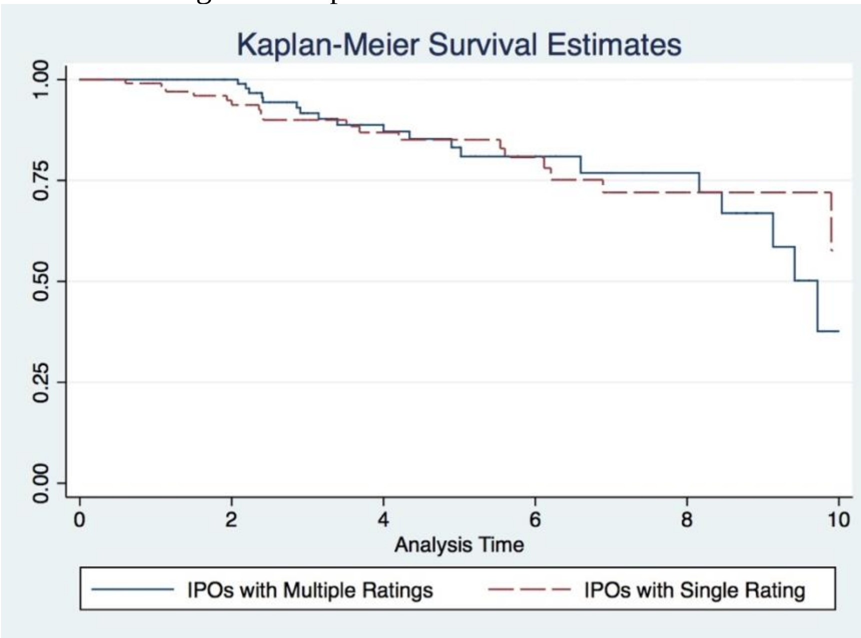

Figure 2. Nelson-Aalen Cumulative Hazard Estimates

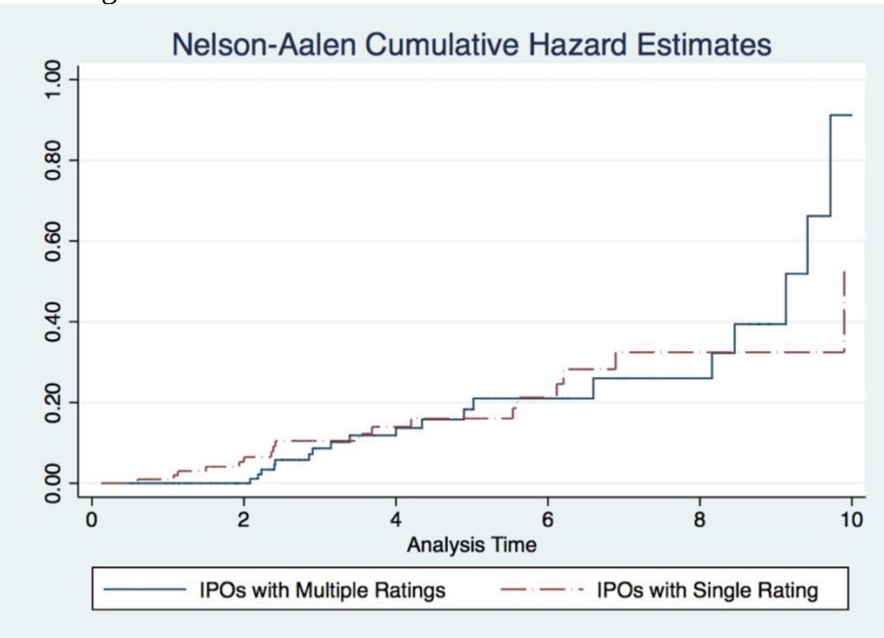

Table 8: Endogeneity Control – Propensity Score Matching

The table reports the average treatment effect of the treated (ATET), that is the conditional probability of having multiple ratings rather than a single rating, for the initial returns in companies with multiple ratings versus those with single ratings, controlling for the endogeneity of multiple credit ratings using propensity score matching. The sample consists of 313 rated IPOs from 1997 to 2016 in the U.S. stock market. Because of missing values, the actual number of observations is below 313. *Multiple Ratings* is set to 1 if the company has been awarded two or more ratings, and 0 otherwise. The outcome variable is IPO *Initial Return*, defined as the percentage change between the first-day closing price and the offer price. The variables used for matching are *Overhang*, *Underwriter Reputation*, *Auditor Reputation*, *Primary Shares*, *Log Proceeds (Size)*, *Log Age*, *Timelag*, *Internet Firm*, and *CRL cut-off*. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix A. The maximum caliper width and the number of matches per observation is set to 0.01 and 1 respectively. Standard errors are reported in parentheses below the coefficient estimates.

	Multiple vs Single Rating
	Initial Return
	(1)
ATET	
(Multiple vs Single)	-6.72***
	(2.25)
Number of Observations	289