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

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Abstract

We examine initial public offerings (IPOs) with single, multiple, and no credit ratings. We document a beneficial effect of credit ratings on IPO underpricing, which is amplified by the existence of multiple credit ratings. Multiple ratings also reduce the extent of filing price revisions. Credit rating levels matter for IPOs with more than one rating but not for those with a single rating. Firms with multiple credit ratings also have higher probabilities of survival than those with a single or no rating. Finally, IPOs awarded a first credit rating between BB and BBB are more likely to seek an additional rating.

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

JEL Classifications: G10, G14, G39.

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In May 2013, William Lyon Homes, a construction company operating in California, was going through the process of filing the price range for its upcoming equity issue. Noticeably, the company announced its IPO while having multiple ratings, assigned by the world's most prestigious credit rating agencies (CRAs). In particular, Moody's assigned William Lyon Homes a rating of B3, whereas Standard & Poor's (S&P) gave it a B- rating. The company managed to raise roughly $218 million while incurring a modest underpricing of 2%. The question that arises is whether the possession of ratings from a variety of CRAs at least partially reduces IPO underpricing.

While the list of rated prospective issuers is lengthy, literature on the effect of multiple ratings on IPO performance is as yet sparse. A plethora of studies[1] suggest that the dissemination of information, or uncertainty reduction, is to the advantage of the least-informed parties in an 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 remains a field that requires further investigation. Our research is motivated by the lack of related empirical evidence as well as by Sangiorgi and Spatt (2017), who argue that multiple ratings are socially optimal if the benefit of the additional rating outweighs the cost of information production. This argument aligns with the "shopping hypothesis" and "information production hypothesis" of Bongaerts et al. (2012). 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 the equivalent study for IPOs. However, both studies focused only on S&P ratings. We extend this literature by investigating the 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, 2017).

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 the necessity to acquire CRA ratings prior to the IPO in order to achieve a higher offer price and reduce IPO underpricing. This raises several interesting questions. Do the multiple ratings have any 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 any incremental effect of investment grading on IPO performance? Are companies with a credit rating on the threshold of investment grade more likely to acquire multiple ratings in the period of going public? Finally, do multi-rated firms experience better survival chances than firms with a single or no rating?

Further, we are 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 credit rating agencies

[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).

ahead of the flotation day is an important signal to market participants. To investigate this we employ a comprehensive and large sample of U.S. IPOs covering a period that spans from 1 January 1997 to 31 December 2016. Based on information retrieved from the Bloomberg database, 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 conjecture that multiple credit ratings improve first trading day performance. Importantly, multiple credit ratings have a much greater negative impact on underpricing than is the case for a single rating.

Our study is related to the work of An and Chan (2008), Bongaerts et al. (2012), Kedia et al. (2014), and Sangiorgi and Spatt (2017). An and Chan (2008) examine the effects of credit ratings by S&P on IPO pricing; 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. Sangiorgi and Spatt (2017) develop a framework to understand the existence of multiple ratings and their information content at various levels. Our work is also related to the economics literature on strategic contracting when the information revealed affects a third party, which relates to a wide range of microeconomics issues.

We begin our analysis by regressing the level of initial returns according to the presence of multiple credit ratings, alongside a set of control variables that are commonly employed in the relevant literature. Our baseline results show that, while one credit rating reduces the amount of money "left on the table", two or three ratings have an even greater effect on 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. In other words, the higher the average credit rating level for companies with multiple ratings the lower is the level of underpricing. In contrast, the rating level of single-rated issues has a substantially lower effect on the level of IPO underpricing. This might be attributed to the 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 of 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.

Next, we investigate the impact of multiple credit ratings on the book-building process. We focus on the effect of multiple credit ratings on both the extent and direction of the revisions 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. Again, this suggests that the existence of multiple credit ratings matters and the existence of a single credit rating does not.

Finally, we examine the survival rate of IPO firms with either a single or multiple credit ratings. We examine 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 issue that arises is endogeneity. The debt market has traditionally relied heavily on credit ratings to determine the suitability and riskiness of fixed-income investments (see Bongaerts et al., 2012). Certain legislative acts may affect the decision to seek credit ratings. Behr et al. (2018) examine how the U.S. Securities and Exchange Commission (SEC) regulations affected credit rating. Their study is part of a growing literature that shows how competition in the rating industry and the use of rules and regulations impact credit ratings, both theoretically and empirically (see, for example, Becker and Milbourn, 2011; Bongaerts et al., 2012; Bolton et al., 2012; Bar-Isaac and Shapiro, 2013; Manso, 2013; Opp et al., 2013; Bruno et al., 2016). Blume et al. (1998), Alp (2013) and Baghai et al. (2014) argue that credit ratings became more strict over time. Opp et al. (2013) developed a theoretical model assessing the effect of regulations based on ratings and state that "relative to the equilibrium without regulations, the rating agency has an incentive to rate more firms highly." Hence, we instrument the presence of credit ratings with the Dodd–Frank Wall Street Reform and Consumer Protection Act. 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 the existence of multiple credit ratings matters because they have beneficial effects on IPO performance and the price revision of the filing price, whereas single ratings have much less of an effect or even no effect at all. Second, our study refines the results of An and Chan (2008), who limit themselves to S&P ratings and ignore multiple credit ratings. While we confirm the results from An and Chan (2008), our results differ from theirs as follows: first, we document the importance of the credit rating level. However, this effect is only observed for IPOs with more than one credit rating. Second, while we also find that credit ratings reduce the degree of price revision, this effect is again only evident for IPOs with multiple credit ratings. Third, our study offers new insights into 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 seems to stem mainly from firms with multiple credit ratings at investment grade.

The rest of this paper is organized as follows: Section I reviews relevant studies from the IPO and credit rating literature; Section II develops our hypotheses; Section III identifies the data sources, describes the sample selection and reports summary statistics; Section IV outlines the methodology. We present the outcomes of the empirical analysis in Section V, and Section VI examines the survivorship of multi-rated IPOs. To validate our findings, we run a battery of robustness tests in Section VII, while Section VIII deals with endogeneity issues. We conclude our study in Section IX.

I. Literature Review

A. Theoretical Framework

The price determination for a new equity issue takes place in an uncertain environment. Existing research consistently relies on first trading day performance to measure uncertainty. Since Stoll and Curley (1970), Logue (1973) and Ibbotson (1975) provided initial evidence of persistent abnormal returns earned by investors in IPOs, numerous studies have attempted to investigate IPO underpricing, including its causes. The majority of theoretical explanations are based on the asymmetric information among the various equity market players. For example, Rock (1986) and Beatty and Ritter (1986) argue that outsiders consider themselves insufficiently informed about a firm's prospects and therefore ask for price discounts. Relatedly, the book-building process requires input from informed investors. To entice these investors to reveal their privileged information, underwriters have lowered the offer price (Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Spatt and Srivastava, 1991).

An alternative theoretical explanation, which is also based on asymmetric information, attributes value to underpricing and claims that issuers intentionally consent to it. Specifically, Welch (1992), Habib and Ljungqvist (2001), and Demers and Lewellen (2003) argue that a low offer price serves as a marketing tool to make the new offering more attractive to investors. Further, Chemmanur (1993) argues that management allows for high initial returns in order to buy analyst coverage, while other studies (Hughes and Thakor, 1992; Drake and Vetsuypens, 1993; Lowry and Shu, 2002) highlight the importance of a strong first-day close in avoiding lawsuits by new investors.

There is a considerable amount of previous literature that states that third-party certification, provided by prestigious underwriters (see Booth and Smith, 1986; Carter and Manaster, 1990; Carter et al., 1998; Brau and Fawcett, 2006; Chen et al., 2008), 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), delivers a strong positive signal to the markets that the firm going public is worth investing in.

Finally, shifting the perspective from asymmetric information to prospect theory, Loughran and Ritter (2002) argue that issuers, being in a euphoric state from the new wealth created by the IPO sale, willingly overlook the cost of underpricing. However, as documented by Ritter (2008), the total amount of money left on the table in the U.S.A. has been a staggering $159.09 billion over the last thirty-seven years. Thus, any behavioral approach seeking to downplay the importance of effective IPO pricing should be considered with skepticism.

B. Credit Ratings as Information-Transmitting Mechanisms

Ross (1977) suggests that firms of superior quality can identify themselves by increasing their leverage, which is not an option for competitors with a high probability of default. Similarly, Certo et al. (2003) argue that increasing leverage qualifies as a credible signal because it is easily identifiable by market participants but costly for poor-quality firms to imitate.

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 company'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 is of vital importance for a firm, considering that credit ratings not only provide an independent assessment of an organization's creditworthiness but also implicitly 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) argue that because a sufficient number of investors base their investment decisions on credit ratings, other less-informed market participants will follow suit.

II. 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 corporate failures of companies with very high credit ratings, together with the recent 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. The U.S. House Representative, Jacqueline Speier, revealed the blame put on CRAs as she questioned Moody's top management in a 2009 congressional hearing:

"*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?*"

Bolton et al. (2012) report that the lack of trust in the credit rating system stems from the fact that the main source of revenue for CRAs comes from the firms that are under evaluation, because the latter have to pay to obtain a rating. As a consequence, in the oligopolistic market of the CRAs, companies with just one rating are less appealing to investors than those with two or more 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; Flynn and Ghent, 2017).

To date, the effects of multiple credit ratings on IPO performance remain a largely unexplored area. Addressing this gap in the literature, our paper contends that the acquisition of multiple ratings from the world's leading CRAs (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 by "lowering heterogeneity in investor valuations", we argue that securing more ratings significantly enhances outsiders' trust in a firm. This leads us to our first hypothesis:

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

Next, we focus on whether the magnitude of underpricing varies across rating levels. We contend that CRAs not only inform market participants about the company's risk profile but they also provide monitoring services via the so-called "watch procedures", which can 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 actions, 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. Hence, not only the existence of multiple credit ratings, but also their level should 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 price discovery. More specifically, as the book-building 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 price discovery. The magnitude of price revisions is analogous to the information revealed during this procedure. Because credit ratings reduce the information asymmetry around a firm's financial standing, we would expect a lower degree of price revision in their presence. Again, we would 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. Manso (2013) reports that CRAs should focus not only on the accuracy of their ratings but also on the effects of their ratings on the probability of survival of the borrower. One way in which this can be achieved is for CRAs to collect a small fee from the firms being rated. Under this scheme, CRAs become interested in the survival of the borrowing firm, inducing them to select the soft-rating-agency equilibrium. Güntay and Hackbarth (2010) claim that multiple ratings are valuable because they mitigate asymmetric information for risk-averse investors, while Hilscher and Wilson (2016) report that in order for credit ratings to be informative indicators of credit risk they have to mirror the main concerns of a risk-averse investor, that is, the probability of failure and systematic risk. Bongaerts et al. (2012) suggest that fewer firms may opt for multiple ratings unless the marginal CRA can convince the market that its ratings are useful in terms of providing additional information about credit risk. Sangiorgi and Spatt (2017) 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 longer and less likely to default than companies with either a single or no rating.

III. Data and Methodology

A. Sample Selection Criteria

To construct our sample we retrieve from the Securities Data Company (SDC) the whole population of new listings that have been floated on U.S. exchanges for the period of 1 January 1997 to 31 December 2016. Consistent with 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. 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.

Credit rating data are obtained from Bloomberg. The CRAs covered by this study are the three leading U.S. CRAs, namely 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.

B. Sample Identification 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 dot-com bubble burst, had a considerable economic impact, reducing the number of IPOs during 2001–2003 by approximately 80% in comparison to the 1998–2000 period. The IPO market recovered between 2004 and 2007 before plummeting again because of the 2008 financial crisis. The market displayed signs of recovery shortly thereafter (and specifically from 2010 onwards). This upward trend slowed down in 2015 because of a lack of momentum in tech offerings, and healthcare, financial, consumer, and energy sectors all hitting historical lows.

The most-preferred CRA among 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 in 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 to Caa1. Essentially, the credit ratings for the IPOs are concentrated around the border between lower-medium investment grade and non-investment, speculative grade. 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 (2.56%). Moreover, in Panel C of Table 1 we document that for IPOs with two credit ratings (and, in particular, ratings provided by S&P and Moody's only), S&P and Moody's were, respectively, the first to be approached in 43.65% (55 out of 126) and 36.51% of cases. 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, we document that S&P and Moody's, regardless of the timing of the credit rating conferment, issued higher credit rating levels in 52 (41.27%) and 18 (14.29%) of the 126 cases, respectively. This latter corroborates the notion that Moody's is stricter than S&P.

Table 2 reports summary statistics for the entire sample as well as for the rated and unrated new offerings[2]. Specifically, Panel A reports summary statistics for IPO pricing whereas Panel B provides descriptive statistics for the IPO characteristics. Preliminary evidence from Panel A indicates that multi-rated IPOs experience lower levels of underpricing because their mean underpricing is approximately 60% below that of unrated IPOs and 40% less than that of single-rated IPOs[3]. In economic terms, this translates into an increase in proceeds of $16.40 million for the average-sized IPO (not tabulated). Similarly, the existence of credit ratings reduces the magnitude of the filing price revisions. Further, the mean Tobin's Q ratio, a proxy for a company's competitive advantage (see Chung and Pruitt, 1994), of unrated new offerings is almost three times the means of the single- and multi-rated issues, indicating greater growth prospects for firms that have not secured a rating from the CRAs. This is partially explained by the substantial growth expectations of IPOs for information technology companies, which rarely have a credit rating. Finally, multi-rated firms also experience higher levels of investor valuation because their mean of investor valuation is, respectively, 42% and 21% higher than those of firms with a single credit rating or without a rating.

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

[3] We observe that IPOs securing multiple credit ratings have average underpricing of only 9.29% compared to 23.43% and 15.39% for their unrated and single-rated counterparts, respectively.

Panel B of Table 2 documents that multi-rated IPOs are considerably larger than single-rated and unrated ones as evidenced by the mean of gross proceeds, which amount to $363 million for the former and only $346 million and $141 million, respectively, for the latter. This pattern is also evident for average net sales, an alternative proxy for size. The firms with multiple credit ratings are older, with an average age of about 39 years compared to only 17 and 33 years for the unrated and single-rated firms, respectively. Reflecting their better quality, IPOs with multiple credit ratings are more likely to have a Big Four auditor and prestigious underwriters, and are less likely to resort to venture-capital financing, than firms with a single or no rating. With respect to overhang, IPOs with multiple credit ratings appear to have lower percentages of ownership retention by the pre-IPO shareholders. They are also less likely to issue primary shares only. Finally, the average borrowing costs of multi-rated IPOs are 35% and 75% lower, respectively, than those of single-rated and unrated IPOs. The correlation matrix for these variables is presented in Table A1: no severe multicollinearity is detected among them.

IV. Methodology

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

$$Y_i = \alpha + \beta X_i + \gamma CR_i + \varepsilon_i \tag{1}$$

where Y_i is the level of IPO underpricing (or the level of 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. ε_i is an independently and identically distributed (i.i.d.) random variable.

First, we conduct our analysis under a multivariate Ordinary Least Squares (OLS) framework. In order for the coefficients to be unbiased, the γ coefficient needs to be free from feedback effects and thus uncorrelated with ε_i ($Cov(CR_i,\varepsilon_i) = 0$). However, the acquisition of credit ratings is unlikely to be exogenous. It is plausible to assume that an IPO company will seek credit ratings if the benefits, namely the expectation of superior first trading day performance, outweigh the costs of the 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 reports the probability of a firm having at least one credit rating. Specifically, we model this selection equation as follows:

$$CR_i^* = \omega W_i + \mu_i \tag{2}$$

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

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. 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:

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

Similarly, the equation for unrated IPOs is:

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

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

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

where ϕ and Φ represent, respectively, the cumulative and density distribution functions of the standard normal distribution.

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

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

To verify the robustness of our estimates we also employ the two-stage least-squares (2SLS) technique 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 against 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 is replaced by the fitted probabilities we obtained from the reduced form. The use of predicted values is crucial for our analysis. Because the extant literature does not specifically dictate a set of parameters that should be included in Equation 2, this methodology provides a degree of flexibility in the choice of explanatory variables. The reason that we extend our choices beyond those reported in the literature is to eliminate the impact of omitted variables on our results. In addition to the 2SLS model, we use the maximum likelihood estimation (MLE) methodology to calculate the selection and outcome equations concurrently.

V. Empirical Analysis

A. Probability of a Firm Having Credit Ratings

Table 3 reports (by running a probit model) the maximum likelihood estimates of a firm having at least one credit rating. Similarly to An and Chan (2008) and Alissa et al. (2013), we estimate the first-stage regression of the Heckman treatment effect model. In this specification we do not distinguish as yet between single and multiple credit ratings. Our results indicate — and confirm Liu and Malatesta (2006) and Faulkender and Petersen (2005) — that the higher the fraction of companies in the same industry with credit ratings (*Indfrac*), the greater is the likelihood of an IPO company having a credit rating. The proxy for the size of the firm is *Log Sales*. Our estimates show that a company's size is an important determinant of having at least one credit rating. Further, the evidence indicates that IPOs with greater operating experience (*Log Age*) and those with higher levels of *Leverage* have a greater likelihood of possessing at least one credit rating.

B. Credit Ratings and IPO Underpricing

To assess the significance of credit ratings, in Table 4 we consider the effect of at least one credit rating on underpricing for the full sample of firms (N = 4,251). The results are robust to four different econometric techniques: OLS (Specification 1), the Heckman two-stage procedure (Specification 2), the 2SLS approach (Specification 3), and the MLE two-equation treatment model (Specification 4). The dependent variable in all specifications is the first-day return, that is, the difference between the first aftermarket closing price and the IPO offer price, divided by the IPO offer price. Among the regressors we include variables that have been proven to explain much of the variability in returns.

Taken as a whole, all four models in Table 4 suggest that rated IPOs are less underpriced than unrated IPOs. The outputs of the three estimations in Specifications 2, 3 and 4 produce highly significant (at the 1% level) coefficients on the *Rating* variable, while the OLS output in Specification 1 produces a slightly less significant (at the 5% level) coefficient. The Inverse Mills ratio from the Heckman procedure is statistically significant (at the 10% level), which highlights the presence of selection bias. The likelihood ratio verifies the correlation of the residual terms in the selection and outcome equations at the high-significance level of 1%. Finally, the Hausman test, from the 2SLS framework, rejects the hypothesis of no endogeneity[4].

Next, our findings provide further insights into the determinants of IPOs. We obtain a positive and highly significant coefficient on *Overhang*: dilution costs are larger in issues with smaller overhangs, suggesting less underpricing. Providing support to 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. Similarly to An and Chan (2008), IPOs involving primary shares only (*Primary Shares* equaling 1) are more underpriced than IPOs with secondary stocks. The positive sign that we document for the *Revisions* is in line with the "partial adjustment" phenomenon (see Hanley, 1993). In contrast, the negative coefficient on *Log Age* corroborates past research indicating that long-lived enterprises are associated with a greater likelihood of survival and, hence, reduced levels of uncertainty.

Timelag is associated with a negative sign, suggesting that the longer the period between the last day of the stock's public offering and the first day of its listing the smaller is its underpricing. *Internet Firms*, as per Ljungqvist and Wilhelm (2003), are positively related with returns to investors. This is to be expected because these companies are characterized by greater uncertainty and increased asymmetry of information between issuer and underwriter. Finally, *Auditor Reputation* has, at best, a weak impact on underpricing.

C. Multiple Credit Ratings and Initial Returns

In this section we focus on the first trading day performance of multi-rated companies. Our first hypothesis suggests that firms with multiple credit ratings have better IPO performance than those with a single rating or no rating. To explore this we employ the indicator variable *{2} or {3} Ratings*, which indicates those firms that go public with two or three credit ratings. We use the equivalent indicator variable *{1} Rating* for firms with a single credit rating. The aforementioned variables are

[4] Because of space limitations, the likelihood ratio as well as the Hausman test are not tabulated in our subsequent analysis. The results are qualitatively the same as in Table 4. The statistical results are available upon request.

regressed on the level of initial returns while the set of control parameters remains broadly unchanged[5].

Using the whole sample of 4,251 firms, we document in Table 5 that the two key binary variables are typically highly significant and always negative across all four estimation techniques. In support of Hypothesis 1, all our specifications suggest that IPOs with multiple credit ratings have lower underpricing than those with one or no rating. Indeed, our estimates reveal that the regressor's magnitude for IPOs with multiple ratings is much greater than that for IPOs with just one rating. More specifically, IPOs with multiple ratings have about 9.90 percentage points less underpricing than companies with no rating (see Specification 1). Economically, this translates into an average increase in proceeds of $17.47 million for an average-sized IPO firm[6]. These results support Hypothesis 1.

D. 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 one or no credit rating. To test the validity of Hypothesis 2, we examine whether there is a negative effect from a higher credit rating level on underpricing and whether this effect is greater in the presence of 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 multi-rated firms, and the latter the credit rating level of single-rated firms.

To explore further the channels by which the levels of credit rating affect IPO underpricing, we review the resulting coefficients from the following four estimation techniques: OLS (benchmark model) in Specification 1, the 2SLS approach in Specification 2, the Heckman two-stage procedure in Specification 3, and the MLE two-equation treatment model in Specification 4 (see Panel A of Table 6). Our results are robust across all models and suggest that IPO companies with higher rating levels provided by a single rating agency (*CRL {1 Rating}*) are not necessarily underpriced any less than firms with lower levels of credit rating. In contrast, we find a highly significant (at the 1% level) and negative coefficient for companies with higher (average) credit rating levels issued by two or more CRAs, reflecting the greater capacity of multiple credit ratings to reduce IPO underpricing. In economic terms, this means that if we increase the credit rating level for multi-rated companies by 1% the level of initial underpricing decreases by 0.91%. Alternatively, this corresponds to an average

[5] Throughout our analysis, the selection equations in the Heckman two-stage procedure incorporated additional variables, i.e. *Growth, Aged, Leverage, Tangibility* and *Log Shares*. However, their coefficients were highly insignificant and they were thus omitted from the tables.

[6] The average for the IPO proceeds is $176.50 million.

increase in IPO proceeds of approximately $1.61 million. To summarize, these results support our Hypothesis 2.

Similar to Aktas et al. (2018), who find no evidence that companies rated at the investment-grade cut-off curtail their acquisition behavior, we consider whether companies with credit levels between BB and BBB, that is, those on the borderline between investment and non-investment grade (referred to as the "CRL cut-off" in what follows), seek to obtain more than one credit rating. Panel B of Table 6 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. By contrast, of the remaining 256 out of 313 rated firms that did not receive a first rating at the investment-grade cut-off, only 97 obtained an additional rating (or 38%)[7]. This suggests that companies at the investment-grade cut-off are more likely to seek multiple credit ratings to improve their creditworthiness. Panel C shows that 10 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 2 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)[8].

E. Multiple Credit Ratings and IPO Price Revision

In this subsection, we study the link between multiple credit ratings and the degree of IPO price revision (*Revisions*) during the book-building process for the full sample of firms (N = 4,251). The dependent variable is the difference between the offer price and the midpoint of the initial filing price range, divided by the offer price. The two key independent variables under examination are the indicator variables *{2} or {3} Ratings* and *{1} Rating*[9]. Table 7 shows that both estimated coefficients display the expected negative sign; however, only the one for two or more credit ratings is statistically significant (at the 1% level). This outcome supports our Hypothesis 3, which states that multiple credit ratings decrease the degree of filing price revisions more than a single or no credit rating. The findings pertaining to the control variables are consistent with previous literature.

[7] In our sample we have 144 multi-rated firms. Of those 144 firms, 57 received a first credit rating level at the investment-grade cut-off whereas the remaining 97 firms obtained a first rating outside the investment-grade cut-off area. Because of space limitations, the numbers are not tabulated.

[8] Additional results retrieved from probit and logit models are not tabulated because of space limitations, but are available upon request.

[9] These take a value of 1 if the firm has multiple credit ratings or a single credit rating, respectively, and 0 otherwise.

VI. The Impact of Multiple Credit Ratings on the Survivorship of IPOs

IPOs are known for their underperformance in the long run, with a large proportion of them failing to survive during the first three years (e.g. Espenlaub et al., 2012; Gerakos et al., 2013; Gounopoulos and Pham, 2018). Such an environment may create pressure on CRAs, with respect to the confidence they display and the ratings they provide to firms with high leverage but a relatively short history of published financial statements. To assess whether this is indeed the case, we explore the likelihood of survival for companies that decide to go public with multiple credit ratings and compare it with companies with either a single rating or no rating. To determine whether a firm that was listed with multiple ratings has a better chance of survival, we estimate a hazard model (see Appendix B for more details of the methodology).

In Panel A of Table 8 we provide the distribution of IPOs over the different types of survival status (i.e. failed, acquired, or survived) until December 2016, as well as for five years after going public (see also Figures 1 and 2). As of December 2016, 17% of the IPO firms had failed and 38% had been acquired; the remaining 45% had survived. In addition, companies with multiple credit ratings experienced lower failure (higher survival) rates than companies with either a single rating or no rating. In particular, up until 2016, approximately 12% of multi-rated companies failed, whereas those companies with a single or no rating experienced significantly higher failure rates (15% and 17%, respectively). Correspondingly, in the same period, 49% of multi-rated firms survived, whereas companies with a single or no rating experienced lower survival rates (approximately 46% and 44%, respectively). Similar patterns are documented for the five years after going public[10].

The Kaplan–Meier and Nelson–Aalen curves in Figures 1 and 2 provide further insights. In Figure 1, the survival function five years after the IPO for companies with multiple ratings lies above the equivalent functions for firms with no rating or just a single rating. Time widens the gap between the different categories of firm. In particular, the probability of a multi-rated firm surviving five years after the IPO is approximately 88%, while that of firms with no rating or a single rating is substantially lower, at approximately 78% and 80%, respectively. This gap between multi-rated companies and single or non-rated companies continues to hold ten years after the IPO, with a survival rate of about 82% for multi-rated companies and 75% for non-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 those for the IPOs with a single or no credit rating, and the corresponding

[10] In our sample the years with the highest number of failures and survivals are 1999 and 1997, respectively. The manufacturing industry has the highest failure rate (around 25%) while the entertainment services industry has the highest likelihood of survival, at almost 58.5%. Because of space limitations, these results are not tabulated but are available upon request.

vertical distance between the curves increases substantially over time. More specifically, multi-rated and unrated or single-rated firms have likelihoods of failure of approximately 10% and 17–20%, respectively, five years after going public. These results support our Hypothesis 4 that firms with multiple ratings are more likely to survive and less likely to default.

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 8. In Specification 1, the main coefficient of interest is that of *{2} or {3} Ratings*, which is negative and statistically significant at the 1% level. This result indicates that IPO companies with multiple ratings have a lower probability of failure and hence a longer survival time in comparison with IPO companies with either one or no rating. The latter result corroborates the results obtained from the non-parametric analysis above, and provides further support to our 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 failure risk for companies with a single or no credit rating.

Further, we introduce a new control variable, *Borrowing Cost*, that serves as a proxy for a 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 a credit rating agency's role in evaluating companies' ability to pay back their debts (Ivashina and Scharfstein, 2010). Its coefficient is significant and positive at the 5% level. This means that if a company's cost of borrowing increases by one standard deviation, its risk of failure will increase and hence its survival time shortens. The hazard ratio of borrowing costs is 1.06, indicating that for each increase in borrowing costs by one standard deviation, the company's failure rate rises by 6%.

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

VII. 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 or no rating. In this section, we conduct several additional tests to assess the robustness of our findings.

A. 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) confirm systematically larger abnormal returns for investment-grade firms compared to those with speculative ratings. Following Helwege and Turner (1999), we initially construct a binary variable, which takes the value 1 for firms with (single or multiple) credit ratings of at least BBB- from S&P and Fitch (and Baa3 from Moody's), and 0 otherwise (see Panel A of Table 9).

Panel A of Table 9 reports the coefficients that measure the effect of *Investment Grade* on the level of IPO pricing for the full sample of firms (N = 4,251)[11]. Invariably, the three estimation methods employed in Specifications 1 to 5 generate significant (at the 5% level) coefficients for *Investment Grade*, and with the hypothesized negative sign. Furthermore, the coefficient magnitudes are broadly consistent with each other. Previous evidence from An and Chan (2008), based on only S&P ratings, 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, which appears robust across different specifications and estimation methods. In other words, we find that firms with an investment-grade rating are associated with substantially lower levels of IPO underpricing. Economically, this translates into an average increase in IPO proceeds of approximately $18.85 million.

To further validate the robustness of our results and to focus our attention on the difference between single and multiple ratings, we generate two new indicator variables, namely *Investment Grade {1 Rating}* and *Investment Grade {2 and 3 Ratings}*. The former takes the value 1 if the firm acquired an investment-grade rating but possesses only one credit rating, whereas the latter takes the value 1 if the firm received ratings from two or more CRAs and at least one of the ratings is at investment grade. Our primary goal is to analyze in depth whether multiple ratings, including at least one rating at investment grade, reduce the level of IPO underpricing more than their single-rated counterparts at investment grade. The results tabulated in Panel B of Table 9 suggest that an investment-grade rating for companies with only one credit rating has no impact on the level of IPO pricing (similarly to An and Chan, 2008). However, firms with at least two credit ratings, including one at investment grade, leave significantly less money on the table. In terms of economic significance, this means an average increase in proceeds of approximately $29.74 million. Thus, we provide additional evidence that an investment-grade rating does matter for multi-rated companies. These results qualify our findings in Panel A of Table 9.

[11] The other control variables, such as the *Auditor Reputation* and *Internet Firm* were highly insignificant, and are hence omitted from the models.

B. Propensity Score Matching

To account for potential endogeneity, we employ a propensity score matching procedure. In a first step, we estimate the propensity score, which is the conditional probability of receiving treatment (having multiple ratings) given a firm's pre-treatment characteristics, for all the IPOs via a probit regression.

Furthermore, we include filing price revisions as well as various IPO characteristics in the probit regression, that is, *Auditor Reputation*, *Firm Age*, *Overhang*, *Underwriter Reputation*, *Venture Capital*, *Proceeds*, and *Primary Shares*. Table 10 presents the results for the average treatment effect of the treated (ATET) for those IPO firms with either single or multiple ratings compared to those with no credit rating. The results support our Hypothesis 1. First, our estimates document that IPO firms with multiple ratings experience less underpricing than those with no rating. The magnitude of the estimate is also economically meaningful, suggesting that a credit rating reduces underpricing by 11.77%. Economically, this translates into an average increase in proceeds of $20.77 million.

In contrast, the corresponding reduction in the money left on the table for single-rated firms is only 7.64%. The coefficients in all of these estimations stay qualitatively alike and are consistent with our Hypothesis 1.

C. Further Robustness Tests

Following previous literature, we conduct additional robustness tests that include the following: (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); (3) censoring underpricing at the 1st and 99th percentiles, and alternatively at the 5th and 95th percentiles, to account for outliers[12].

VIII. Instrumental Variable Analysis

We argue that companies with multiple ratings achieve lower underpricing than those with a single or no rating. However, the relation established so far between underpricing (as well as filing price revision) and credit ratings might be due to omitted variables. For instance, in response to the 2008 global financial crisis, the U.S. Congress passed the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 that caused broad changes to the CRA market. Indeed, many investors and analysts believed that CRAs inflated credit ratings and hence were partially to blame for the financial

[12] Because of space limitations, these results are not tabulated but are available upon request.

collapse. In response, the Dodd–Frank Act increased CRAs' liability for the issuance of dubious ratings. Hence, the Dodd–Frank Act might have had an effect on the way both CRAs and firms operate. For example, Dimitrov et al. (2015) find that, following the Dodd–Frank Act, corporate bond credit ratings are lower, less accurate and less informative. To explore further this aspect we utilize a binary variable, that takes a value of 1 for the period after the legislation of the Dodd–Frank reform, and 0 otherwise, and analyze its effects following the instrumental variable (IV) approach[13]. Our approach follows extant literature (e.g. Chemmanur et al., 2018; Coles et al., 2017). In the following subsection, we explain our methodology and results.

A. Empirical Results from Instrumental Variable Analysis

Initially, we run two different probit regressions to estimate the probability of a company having (i) multiple credit ratings (MCR), and (ii) a single credit rating (SCR). In the second-stage regression we regress the level of IPO underpricing on the predicted value of the probability of credit ratings (*Predicted(Rating)*) retrieved from the first-stage estimation, as well as a group of control variables (see Appendix B for more details of the methodology). The results are reported in Table 11.

Our findings indicate that the Dodd–Frank instrument is linked to the probability of multiple credit ratings (Specification 1) as well as the probability of a single credit rating (Specification 3). Notably, the coefficient of the instrument in the first-stage regression is significant and negative at the 5% level or better. The value of the F-statistic for the first-stage regression from Specifications 1 and 3 (i.e. 180.02 and 165.36, respectively) exceeds the critical value of 10. Our projections show that since 2010, when the Dodd–Frank Act came into force, the probability of companies obtaining credit ratings has reduced slightly. In addition, from the second-stage regression we ascertain a negative and highly statistically significant (at the 1% level) link between *Predicted(Rating)* and the level of underpricing. Comparing the magnitude of the coefficients in Specifications 2 and 4 for the key explanatory variable (i.e. *Predicted(Rating)*), we notice that the one corresponding to the firms with multiple credit ratings (MCR) has the higher magnitude. In other words, multiple ratings reduce underpricing more than a single or no rating. This finding corroborates our Hypothesis 1.

Finally, for robustness purposes, we utilize in the second-stage regression of our IV analysis an additional dependent variable, the filing price revision[14]. The parameter estimates[15] (the findings are similar to the ones reported in the paragraph above) show that multiple ratings reduce the levels of filing price revision more than a single or no rating. This result supports our Hypothesis 3.

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[13] To explore further the robustness of our results (i.e. multiple ratings reducing IPO underpricing more than single ratings) we utilized alternative instruments, that is, the median as well as the mean of the credit rating level by industry for each year. The findings under the IV approach corroborate our results as described in Section V, and are available upon request.

[14] See Appendix A for the detailed definition of this variable.

[15] Because of space limitations the results are not tabulated but are available upon request.

IX. Conclusion

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

Our study contributes to extant literature and, in particular, to An and Chan (2008). The latter study focuses on S&P credit ratings only. While it finds that the existence of a credit rating reduces IPO underpricing, the level of the credit rating does not seem to matter. In contrast, our study considers multiple credit ratings by the three main CRAs, that is, 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 find that Moody's rarely awards a higher rating than S&P, while in approximately 45% of the cases the CRAs (that is S&P and Moody's) awarded the same rating. Based on 4,251 U.S. IPOs for the period of 1 January 1997 to 31 December 2016, we find the results set out below.

First, multiple credit ratings reduce both IPO underpricing and the levels of filing price revision significantly more than a single credit rating. Second, while we confirm the finding of An and Chan (2008) that the level of a single credit rating does not affect IPO underpricing, the (average) level does matter when an 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 possess multiple ratings. This suggests that such firms request a second credit rating to certify further their quality or to attempt to surpass the cut-off point. Our results reveal that firms just below investment grade do not receive an upgrade to 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 one previously acquired. Fourth, our findings highlight that multi-rated firms with at least one rating at investment grade benefit from significantly reduced levels of IPO underpricing, whereas we find no evidence that firms with just one rating at investment grade experience any significant influence on the level of IPO underpricing. Finally, firms with more than one credit rating have a greater chance of survival than firms with only one or no credit 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, which in turn is confirmed by the greater likelihood of survival of firms with more than one credit rating.

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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 document.
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 and 3 Rating}	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.
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 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 employing 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
Aged	Binary indicator that equals 1 if the company was at least five years old on the day of the IPO, and 0 otherwise.
Growth	Research and development expenditures divided by net sales.
Industry Fraction (Indfrac)	The logarithm of 1 + the fraction of firms in the same industry with credit 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 dot-com 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: Analysis Processes

A. Instrumental Variable Analysis Process

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

$$Prob(Credit\ Rating = 1)_{it} = a_0 + a_1(Dodd - Frank\ Act)_{it} + a_3 X_{it} + \varepsilon_{it} \quad (7)$$

$$IPO\ Underpricing_{it} = \beta_0 + \beta_1 Predicted(Credit\ Rating)_{it} + \beta_2 Z_{it} + \varepsilon_{it} \quad (8)$$

In the first-stage regression model of our IV approach (see Equation 7), we regress the probability of credit-rating existence (either multiple or single or both) on the instrument, *Dodd–Frank Act* and another eight independent variables X_{it} namely, *Indfrac*, *Tangibility*, *Log Shares*, *Log Sales*, *Growth*, *Profit*, *Aged* and *Leverage* (see Appendix A for the definitions of the variables).
In the second-stage regression (see Equation 8) we regress the level of IPO underpricing (or filing price revisions as a robustness check) on the predicted value of the probability of credit-rating existence retrieved from the first-stage estimation, as well as on a group of control variables Z_{it}.

B. Survival Analysis Process

Survival analysis is an econometric technique that has been utilized extensively in previous literature in order to examine 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 frameworks, such as a cross-sectional logistic model, lies in its ability to account for both occurrence and time-to-event. Furthermore, survival analysis could examine both censored and time-series data in different horizons (LeClere, 2000; Shumway, 2001). The time window varies for each of the firms in our sample depending on the IPO date. In particular, IPO firms are tracked until the end of 2016. Hence, an enterprise with an IPO early in the year 2000 is tracked for 17 years, whereas a company that went public in 2012 is tracked for just five years.

In this study, in order to analyse the link between multi-rated companies and IPO survival, we employ both non-parametric and semi-parametric estimation procedures. The non-parametric ones will allow us to examine and compare the survival rates as well as the failure risks of multi-rated IPOs and those with either no credit rating or just one. Thereby, we will be able to determine whether or not multiple ratings benefit firms' survival performance.

The survival function projects the probability that a firm survives up to a specified time. For example, if multiple ratings can increase the survival rate of an issuing firm, then the curve of the survival function for multi-rated companies will be above the curve of firms with either no rating or just one. 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 either one credit rating or none.

The estimated hazard function returns the conditional probability of failure given that the enterprise survived up to a specified time period. In our analysis, this means that if multiply rating companies can diminish the risk of failure, then the hazard function for such multi-rated IPOs will be below that of firms with no credit rating or just one. 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 could 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:

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

where $h_0(t)$ represents the hazard function, and t the time-to-failure (for instance, the time to 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 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 represents firms that have been awarded 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 (expressed by *Controls*). More specifically, we introduce to our regression variables such as *Primary Shares*, *Filing Price Revisions*, *Venture Capital*, *Profit*, *Aged*, *Leverage*, *Industry Fraction*, *Timelag*, and *Underpricing*, and the dummy variables *Internet Firm, Technology IPO*, and *Dotcom [crisis] Period*[16].

[16] In addition, we included *Auditor Reputation*, *Log Proceeds*, *Underwriter* and *Log Age* of the firm; however, the estimated coefficients were highly insignificant and hence suppressed from the results.

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 A: Distribution Across Time of Rated and Unrated IPOs

	Total	Rated IPOs		Unrated IPOs		S&P		Moody's		Fitch	
Year	**Sample**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
1997	500	16	3.20	484	96.80	12	2.40	4	0.80	7	1.40
1998	311	12	3.86	299	96.14	12	3.86	4	1.29	0	0.00
1999	495	30	6.06	465	93.94	24	4.85	18	3.64	4	0.81
2000	392	29	7.40	363	92.60	23	5.87	15	3.83	5	1.28
2001	88	10	11.36	78	88.64	7	7.95	5	5.68	2	2.27
2002	80	13	16.25	67	83.75	10	12.50	4	5.00	4	5.00
2003	79	11	13.92	68	86.08	11	13.92	4	5.06	1	1.27
2004	234	20	8.55	214	91.45	14	5.98	13	5.56	4	1.71
2005	210	24	11.43	186	88.57	21	10.00	11	5.24	0	0.00
2006	220	20	9.09	200	90.91	17	7.73	14	6.36	2	0.91
2007	271	17	6.27	254	93.73	10	3.69	10	3.69	3	1.11
2008	43	2	4.65	41	95.35	2	4.65	2	4.65	0	0.00
2009	62	10	16.13	52	83.87	7	11.29	9	14.52	2	3.23
2010	165	16	9.70	149	90.30	11	6.67	7	4.24	8	4.85
2011	132	12	9.09	120	90.91	10	7.58	7	5.30	2	1.52
2012	156	9	5.77	147	94.23	6	3.85	4	2.56	4	2.56
2013	231	27	11.69	204	88.31	18	7.79	14	6.06	4	1.73
2014	302	24	7.95	278	92.05	20	6.62	15	4.97	3	0.99
2015	175	8	4.57	167	95.43	6	3.43	6	3.43	1	0.57
2016	105	3	2.86	102	97.14	3	2.86	2	1.90	0	0.00
Total	**4,251**	**313**	**7.36**	**3,938**	**92.64**	**244**	**5.74**	**168**	**3.95**	**56**	**1.32**

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

Credit Rating Category	S&P N	S&P %	Moody's N	Moody's %	Fitch N	Fitch %
B categories (B+, B-, B, B1, B2, B3)	150	47.92	112	35.78	8	2.56
C categories (CCC+, CCC-, CCC, Caa1, Caa2, Caa3, DDD, DD)	7	2.24	18	5.75	9	2.87

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

This table provides summary descriptive statistics for the sample of 4,251 IPOs that were floated on the U.S. stock exchanges over the period January 1, 1997 to 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 with (either single or multiple) and without credit ratings. Statistical tests for differences in means for each IPO pricing and IPO characteristics are also presented. The definitions of all variables are provided in Appendix A.

Panel A: IPO Pricing

	Full Sample (N = 4251)				IPOs With Single Credit Ratings (N = 169)				IPOs Without Credit Ratings (N = 3938)				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	6.67	-97.60	397.60	15.39	6.74	-21.50	219.20	23.43	6.82	-97.60	397.60	9.29	5.22	-47.29	122.83	0.00
	(48.63)				(31.01)				(49.64)				(19.81)				
Filing Price Revision	0.24	0.00	-86.1	717.30	-0.25	0.00	-26.66	33.33	0.38	0.00	-86.10	717.40	-3.17	0.00	-47.06	27.27	0.07
	(22.70)				(11.49)				(23.33)				(12.48)				
Tobin's Q	4.67	1.16	0.00	75.40	1.51	0.86	0.00	23.96	4.97	2.07	0.00	75.40	1.65	0.79	0.00	7.36	0.00
	(8.97)				(2.90)				(9.30)				(0.98)				
Investor Valuation	1.31	0.97	-0.90	7.79	1.02	0.96	-0.13	2.94	1.19	0.96	-0.90	7.73	1.44	0.94	-0.01	7.79	0.00
	(1.11)				(0.87)				(1.12)				(1.20)				

Table 2 (Continued)

Panel B: IPO Characteristics

	Full Sample (N = 4251)				IPOs With Single Credit Ratings (N = 169)				IPOs Without Credit Ratings (N = 3938)				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	346.04	190.00	8.25	4600.00	140.94	73.50	4.00	4133.33	363.10	206.50	11.40	3010.00	0.00
	(295.81)				(558.32)				(247.62)				(501.70)				
Sales	507.32	65.25	0.22	29234.00	1315.76	375.53	1.16	26420.00	408.93	56.24	0.22	29234.00	1755.00	504.45	0.00	24788.00	0.46
	(1875.54)				(2908.73)				(1659.14)				(3510.00)				
Firm Age	18.24	8.00	1.00	224.00	32.79	21.00	1.00	149.00	16.77	8.00	1.00	224.00	38.93	26.00	1.00	165.00	0.00
	(26.44)				(34.08)				(24.95)				(37.29)				
Auditor Reputation	0.73	1.00	0.00	1.00	0.78	1.00	0.00	1.00	0.72	1.00	0.00	1.00	0.85	1.00	0.00	1.00	0.00
	(0.44)				(0.35)				(0.45)				(0.36)				
Underwriter	0.49	0.00	0.00	1.00	0.72	1.00	0.00	1.00	0.48	0.00	0.00	1.00	0.83	1.00	0.00	1.00	0.00
	(0.50)				(0.44)				(0.50)				(0.38)				
Venture Capital	0.50	0.00	0.00	1.00	0.12	0.00	0.00	1.00	0.42	0.00	0.00	1.00	0.06	0.00	0.00	1.00	0.00
	(0.50)				(0.33)				(0.49)				(0.24)				
Primary Shares	0.72	1.00	0.00	1.00	0.68	1.00	0.00	1.00	0.73	1.00	0.00	1.00	0.55	1.00	0.00	1.00	0.00
	(0.45)				(0.47)				(0.45)				(0.50)				
Overhang	5.09	2.8.0	-0.87	209.97	3.86	2.84	-0.87	54.15	5.22	2.82	-0.52	209.97	3.19	2.36	0.15	15.54	0.00
	(10.20)				(5.55)				(10.53)				(2.62)				
Cost of Borrowing	0.90	0.63	-19.00	1180.35	0.37	0.21	-2.01	14.80	0.95	0.69	-19.00	1180.35	0.24	0.13	-0.78	5.49	0.00
	(27.37)				(1.47)				(28.71)				(0.81)				

Table 3: Probit Estimates of the Probability of Possessing a Credit Rating

The table reports the results of a probit regression that examines the probability of credit ratings for a sample of 4,251 U.S. IPOs from January 1997 to December 2016. The dependent variable is a binary variable that takes the value 1 if the firm has at least one credit rating and 0 otherwise. Because of missing values, the actual number of observations is below 4251. Specification 1 reports the estimated coefficients, and Specification 2 the Z-statistics. All the variables are defined in Appendix A. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLE	Coefficient -1	Z-statistic -2
Indfrac	4.68***	6.33
Tangibility	0.12	0.91
Log Shares	0.03	1.42
Log Sales	0.22***	8.73
Growth	-0.01	-1.46
Profit	-0.01	-0.54
Log Age	0.14**	3.39
Leverage	0.06**	1.98
N	2,142	
Pseudo-R^2	0.27	

Table 4: Effect of the Existence of Credit Ratings on IPO Underpricing

This table displays estimates of the four regression procedures of *Rating* and other control variables on IPO underpricing (dependent variable, calculated as the percentage change between the first-day closing price and offer price) based on the 4,251 U.S. IPOs. Because of missing values, the actual number of observations is below 4,251. *Rating* assumes a value of 1 if the firm has at least one credit rating, and 0 otherwise. *Industry Fraction*, *Tangibility*, *Growth*, *Profit*, *Aged* and *Leverage* were utilized as instruments in Specification 3. All variables are defined in Appendix A. The four estimation techniques are: OLS (Specification 1), the Heckman two-stage procedure (Specification 2), the 2SLS approach (Specification 3) and the MLE two-equation treatment model (Specification 4). *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects were taken into account in all specifications.

	OLS	**Heckman**		**2SLS**	**MLE**	
		Selection	**Outcome**		**Selection**	**Outcome**
VARIABLE	-1	-2		-3	-4	
Rating	-4.58**		-17.71***	-28.38***		-13.74***
	(2.16)		(6.52)	(10.48)		(5.54)
Overhang	0.77***		0.79***	0.75***		0.79***
	(0.08)		(0.08)	(0.08)		(0.08)
Underwriter	4.13***		4.31***	6.27***		4.28***
	(1.56)		(1.65)	(1.96)		(1.65)
Auditor Rep.	3.26*		2.30	2.69		2.32
	(1.75)		(1.89)	(1.92)		(1.89)
Prim. Shares	7.98***		7.68***	7.97***		7.71***
	(1.63)		(1.72)	(1.74)		(1.72)
Revisions	1.21***		1.18***	1.17***		1.18***
	(0.06)		(0.06)	(0.06)		(0.06)
Log Age	-1.37**		-1.99***	-0.95		-2.03***
	(0.67)		(0.74)	(0.95)		(0.74)
Timelag	-0.02***		-0.02***	-0.02***		-0.02***
	(0.01)		(0.01)	(0.01)		(0.01)
Internet Firm	18.06***		16.97***	16.38***		17.05***
	(2.52)		(2.66)	(2.72)		(2.66)
2008–2009	-9.97***		-9.92***	-8.87***		-9.91***
	(3.14)		(3.26)	(3.34)		(3.26)
Constant	14.80***	-1.99***	18.67***	15.75***	-1.99***	18.38***
	(2.62)	(0.06)	(2.93)	(3.06)	(0.06)	(2.88)
Industry Fraction		7.07***			7.11***	
		(0.52)			(0.51)	
Profit		0.04***			0.04***	
		(0.01)			(0.01)	
Inverse Mills Ratio			7.47*			
			(4.79)			
Likelihood Ratio Test Against H_0: *ρ=0 (p-value)*						0.00
Durbin–Wu–Hausman Test Against H_0: *Variables are Exogenous (p-value)*				0.02		
Year Fixed Effects	Y	N	N	Y	N	N
Industry Fixed Effects	Y	N	N	Y	N	N
N	3,562	3,190	3,190	3,190	3,190	3,190
Adjusted-R^2	0.21	-	-	0.19	-	-

Table 5: Effect of Multiple Credit Ratings on Underpricing

This table presents our findings on the effect of multiple credit ratings on the level of initial returns for a sample of 4,251 U.S. IPOs over the period 1997–2016. Because of missing values, the actual number of observations is below 4,251. The four econometric techniques are: OLS (Specification 1), the Heckman two-stage procedure (Specification 2), the 2SLS approach (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 variables are the categorical indicators *{2} or {3} Ratings* and *{1} Rating*, that receive the value of 1 if a firm possesses either multiple credit ratings or just a single credit rating prior to the year of IPO, and 0 otherwise. *Indfrac*, *Tangibility*, *Growth*, *Profit*, *Aged* and *Leverage* were utilized as instruments in Specification 3. 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.

	OLS	**Heckman**		**2SLS**	**MLE**	
		Selection	**Outcome**		**Selection**	**Outcome**
VARIABLE	-1	-2		-3	-4	
{2} or {3} Ratings	-9.89**		-28.49***	-44.76***		-15.69***
	(3.45)		(10.62)	(15.80)		(4.88)
{1} Rating	-7.89***		-6.73***	-10.29***		-7.06**
	(2.49)		(2.56)	(3.92)		(2.56)
Overhang	0.57***		0.58***	0.54***		0.58***
	(0.08)		(0.08)	(0.08)		(0.08)
Underwriter	6.99***		7.62***	9.71***		7.58***
	(1.50)		(1.58)	(1.94)		(1.58)
Auditor Rep.	2.12		1.84	1.95		1.85
	(1.67)		(1.80)	(1.83)		(1.80)
Prim. Shares	3.63**		3.03*	2.49		3.08*
	(1.58)		(1.66)	(1.71)		(1.66)
Revisions	1.04***		0.99***	0.97***		0.99***
	(0.05)		(0.06)	(0.06)		(0.06)
Log Age	-0.47		-0.89	-0.004		-0.94
	(0.64)		(0.72)	(0.88)		(0.71)
Timelag	-0.02***		-0.02***	-0.02***		-0.02***
	(0.01)		(0.01)	(0.01)		(0.01)
Internet Firm	8.92***		8.65***	7.95***		8.79***
	(2.47)		(2.58)	(2.66)		(2.58)
Dotcom Period	34.19***		35.64***	36.73***		35.64***
	(1.85)		(1.94)	(2.66)		(1.94)
Constant	9.21***	-2.37***	11.22***	9.13***	-2.37***	10.81***
	(2.52)	(0.08)	(2.79)	(2.88)	(0.08)	(2.75)
Industry Fraction		6.63***			6.69***	
		(0.62)			(0.62)	
Profit		0.04***			0.04***	
		(0.01)			(0.01)	
Inverse Mills Ratio			11.03*			
			(6.64)			
Year Fixed Effects	Y	N	N	Y	N	N
Industry Fixed Effects	Y	N	N	Y	N	N
N	3,562	3,190	3,190	3,190	3,190	3,190
Adjusted-R^2	0.27	-	-	0.26	-	-

Table 6: Effect of Credit Ratings Levels on Underpricing

Panel A documents 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 4,251 U.S. IPOs from 1997 to 2016. Because of missing values, the actual number of observations is below 4,251. The four estimation techniques are: OLS (Specification 1), the 2SLS approach (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, 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}*). *Indfrac*, *Tangibility*, *Growth*, *Profit*, *Aged* and *Leverage* were utilized as instruments in Specification 2. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects were taken into account in all specifications.

Panel A: Effect of the Credit Rating Level on IPOs Underpricing

	OLS	**2SLS**	**Heckman**		**MLE**	
			Selection	**Outcome**	**Selection**	**Outcome**
VARIABLE	-1	-2	-3		-4	
CRL {1 Rating}	-0.66*	-2.99		-0.68*		-0.62*
	(0.35)	(3.04)		(0.37)		(0.37)
CRL {2 and 3 Ratings}	-0.91***	-1.18***		-0.99***		-1.08***
	(0.35)	(0.44)		(0.35)		(0.36)
Overhang	0.58***	0.54***		0.53***		0.46***
	(0.08)	(0.08)		(0.08)		(0.07)
Underwriter	5.69***	8.11***		7.45***		7.61***
	(1.60)	(2.06)		(1.73)		(1.71)
Auditor Rep.	2.31	2.16		2.36		2.29
	(1.78)	(2.01)		(1.99)		(1.97)
Prim. Shares	3.42**	4.25**		3.89**		3.44**
	(1.70)	(1.89)		(1.81)		(1.82)
Revisions	0.98***	0.98***		0.97***		0.96***
	(0.06)	(0.06)		(0.06)		(0.06)
Log Age	-1.05	-0.51		-0.99		-0.02
	(0.68)	(1.12)		(0.85)		(0.80)
Timelag	-0.02***	-0.02***		-0.02***		-0.02***
	(0.01)	(0.01)		(0.01)		(0.01)
Internet Firm	7.73***	7.10***		7.78***		6.94***
	(2.66)	(2.87)		(2.81)		(2.71)
Dotcom Period	31.83***	33.75***		33.42***		31.16***
	(2.02)	(2.18)		(2.15)		(2.08)
Technology IPO	9.47***	8.47***		9.46***		8.82***
	(1.69)	(1.94)		(1.84)		(1.77)
Constant	8.68***	7.05**	1.95***	6.56*	1.85***	6.97**
	(2.75)	(3.35)	(0.12)	(3.81)	(0.11)	(3.14)
Industry Fraction			-2.92***		-2.49***	
			(0.84)		(0.72)	
Profit			0.01		0.006	
			(0.16)		(0.02)	
Aged			0.36***		0.07	
			(0.11)		(0.11)	
Leverage			0.27***		0.32***	
			(0.11)		(0.11)	
Inverse Mills Ratio				14.54		
				(31.72)		
Year Fixed Effects	Y	Y	N	N	N	N
Industry Fixed Effects	Y	Y	N	N	N	N
N	3,573	3,086	3,104	3,104	3,104	3,104
Adjusted-R^2	0.25	0.26	-	-	-	-

Table 6 (Continued)

Panel B documents the number of firms with a first rating from the three CRAs at the borderline between investment and non-investment grade (*CRL cut-off*). In our sample we have 47 firms that satisfy the aforementioned condition. Column 1 displays the number of firms with first ratings between BB and BBB among the three CRAs. Columns 2 to 5 categorize and report the number of firms across each CRA by non-investment- and investment-grade credit rating level, 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 C reports the number of firms with a second rating that was a downgrade, at the same level, or an upgrade, respectively (see Columns 1, 2 and 3). For example, 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 increased or maintained their rating level and only two received a second rating at non-investment grade.

Panel B: Firms With a First Rating Between BB and BBB

	Number of First Ratings Between BB and BBB -1		**Number of Firms With a BB (Non-investment Grade)** -2		**Number of Firms With a BB+ (Non-investment Grade)** -3		**Number of Firms With a BBB- (Investment Grade)** -4		**Number of Firms With a 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 C: 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 7: Effect of Single and Multiple Credit Rating Acquisitions on Revisions of the Filing Price

This table presents our findings on the impact of multiple and single credit ratings on the degree of filling price revision for a sample of 4,251 U.S. IPOs over the period 1997–2016. Because of missing values, the actual number of observations is below 4,251. 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 Filling Price *Revisions*. The main independent variables are the binary indicators that take the value of 1 when a firm obtains one or more credit ratings prior to the year of IPO (*{1} Rating* and *{2} or {3} Ratings*), and 0 otherwise. *Indfrac*, *Tangibility*, *Growth*, *Profit*, *Aged* and *Leverage* were utilized as instruments in Specification 4. All variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses report standard errors.. Industry and year fixed effects were taken into account in all specifications.

	OLS	**Heckman**		**MLE**		**2SLS**
		Selection	**Outcome**	**Selection**	**Outcome**	
VARIABLE	-1	-2		-3		-4
{2} or {3} Ratings	-4.60***		-4.72***		-4.76***	-5.33***
	(1.59)		(1.76)		(1.74)	(2.09)
{1} Rating	-0.72		-0.73		-0.59	-6.53
	(1.46)		(1.59)		(1.58)	(10.37)
Overhang	0.13***		0.11***		0.10***	0.11***
	(0.03)		(0.04)		(0.04)	(0.03)
Underwriter	1.43**		1.55**		1.34*	1.64**
	(0.69)		(0.78)		(0.77)	(0.79)
Auditor Rep.	-0.21		-0.07		-0.17	-0.11
	(0.71)		(0.84)		(0.83)	(0.83)
Prim. Shares	-1.58***		-2.25***		-2.22***	-2.11***
	(0.66)		(0.75)		(0.74)	(0.79)
Log Proceeds	2.03***		2.18***		2.30***	2.345***
	(0.31)		(0.36)		(0.36)	(0.45)
Log Age	-1.01***		-1.40***		-1.33***	-1.30***
	(0.27)		(0.36)		(0.33)	(0.42)
Timelag	-0.06***		-0.06***		-0.06***	-0.06***
	(0.02)		(0.02)		(0.02)	(0.02)
Internet Firm	4.22***		3.78***		4.03***	3.63***
	(1.03)		(1.14)		(1.13)	(1.17)
Dotcom Period	6.45***		6.96***		6.81***	6.86***
	(0.77)		(0.86)		(0.85)	(0.87)
Constant	-35.62***	1.87***	-37.55***	1.76***	-40.25***	-40.35***
	(5.59)	(0.11)	(6.53)	(0.10)	(6.50)	(8.37)
Industry Fraction		-1.67**		-1.54**		
		(0.76)		(0.68)		
Profit		0.06		0.05		
		(0.05)		(0.04)		
Aged		0.28***		0.16		
		(0.11)		(0.11)		
Leverage		0.16*		0.17*		
		(0.07)		(0.09)		
Inverse Mills Ratio			5.61			
			(17.08)			
Year Fixed Effects	Y	N	N	N	N	Y
Industry Fixed Effects	Y	N	N	N	N	Y
N	3,621	3,141	3,141	3,141	3,141	3,075
Adjusted-R^2	0.06	-	-	-	-	0.06

Table 8: 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, as well as 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 Cox proportional hazards model of failure and time-to-failure probability for a sample of 4,251 U.S. IPOs from January 1997 to December 2016. The parameter estimates of the model are reported in Specification 1, while the hazard ratios are reported under Specification 2. Because of missing values, the actual number of observations is below 4,251. The key independent variable is the binary variable *{2} or {3} Ratings*, which is assigned a value of 1 when a firm obtains multiple credit ratings prior to the year of IPO and 0 otherwise. Industry and year fixed effects were considered, whose coefficients are suppressed. All variables are defined in Appendix A. *,**,*** asterisks denote significance levels at 10%, 5% and 1%, respectively. The standard errors are reported in parentheses below the coefficient estimates.

Panel A: Distribution of Failed, Acquired, and Surviving IPOs With Multiple, Single and No Credit Ratings

	From the IPO Date to December 2016								From the IPO Date to Five Years After Offering							
	All IPOs		Multiple credit ratings		Single Credit Rating		No Credit Rating		All IPOs		Multiple Credit Ratings		Single Credit Rating		No Credit Rating	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Failed	568	17.3	17	12.39	20	15.38	531	17.47	349	10.63	7	6.19	11	8.46	328	10.79
Acquired	1,257	38.29	46	38.05	50	38.46	1,161	38.19	666	20.29	23	20.35	29	22.31	652	21.45
Surviving	1,458	44.41	50	49.56	60	46.15	1,348	44.34	2,268	69.08	83	73.45	90	69.23	2,060	67.76
Total	**3,283**	**100**	**113**	**100**	**130**	**100.00**	**3,040**	**100.00**	**3,283**	**100**	**113**	**100.00**	**130**	**100.00**	**3,040**	**100.00**

Table 8 (Continued)

Panel B: Cox Proportional Hazard Model		
	Coefficient	**Hazard Ratio**
VARIABLE	-1	-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)	
Primary Shares	0.14	1.11
	(0.17)	
Filing Price 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	2,598	
Chi-squared	90.34	
Chi-squared Test Probability	0.00	

Figure 1. Kaplan–Meier Survival Estimates

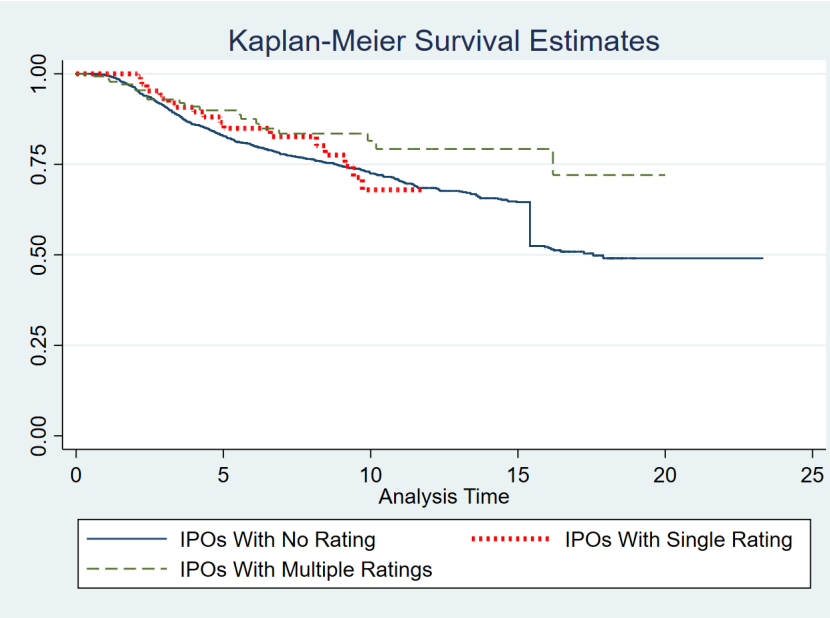

Figure 2. Nelson–Aalen Cumulative Hazard Estimates

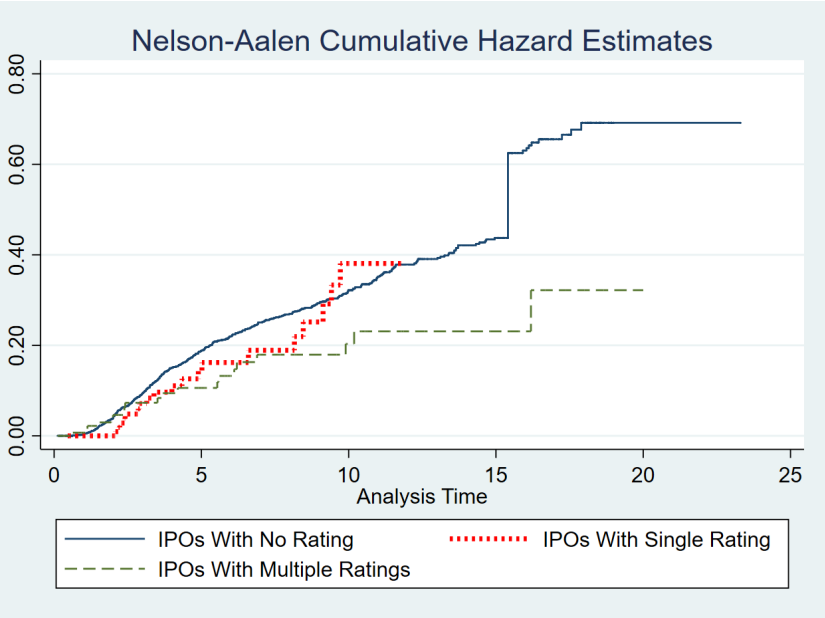

Table 9: Investment Grade and Initial Price Return

Panel A of this table displays the estimation outputs from three econometric techniques for the effect of *Investment Grade* on IPO underpricing for a sample of 4,251 U.S. IPOs from 1997–2016. Because of missing values, the actual number of observations is below 4,251. The binary indicator *Investment Grade* receives the value of 1 if the firm has at least one credit rating and 0 otherwise. All other variables are defined in Appendix A. Three modeling procedures were used: OLS (Specification 1), the Heckman two-stage procedure (Specifications 2 and 3) and the MLE two-equation treatment model (Specifications 4 and 5). *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects were taken into account in all specifications.

Panel A: Effect of Investment Grade on IPO Underpricing

	OLS	**Heckman**		**MLE**	
		Selection	**Outcome**	**Selection**	**Outcome**
VARIABLE	-1	-2	-3	-4	-5
Investment Grade	-10.68**		-12.25**		-12.14**
	(5.42)		(5.67)		(5.52)
Overhang	0.53***		0.48***		0.47***
	(0.08)		(0.08)		(0.08)
Underwriter	4.66***		6.97***		6.86***
	(1.51)		(1.68)		(1.68)
Auditor Rep.	2.94*		2.45		2.56
	(1.68)		(1.97)		(1.97)
Prim. Shares	2.41		3.56**		3.47**
	(1.60)		(1.76)		(1.76)
Revisions	1.04***		1.05***		1.05***
	(0.06)		(0.06)		(0.06)
Timelag	-0.02***		-0.02***		-0.02***
	(0.01)		(0.01)		(0.01)
Dotcom Period	36.98***		38.07***		37.96***
	(1.85)		(2.03)		(2.02)
Constant	9.11***	2.01***	9.36***	2.00***	8.29***
	(2.03)	(0.12)	(2.63)	(0.12)	(2.33)
Industry Fraction		-2.76***		-2.79***	
		(0.83)		(0.85)	
Profit		0.02		0.02	
		(0.02)		(0.02)	
Aged		0.31***		0.31***	
		(0.12)		(0.11)	
Leverage		0.28***		0.28**	
		(0.12)		(0.12)	
Inverse Mills Ratio		-28.38			
		(31.18)			
Year Fixed Effects	Y	N	N	N	N
Industry Fixed Effects	Y	N	N	N	N
N	3,817	3,184	3,184	3,184	3,184
Adjusted-R^2	0.24	-	-	-	-

Table 9 (Continued)

Panel B of this table reports the OLS (Specification 1) regression, the Heckman two-stage procedure (Specifications 2 and 3) and the MLE two-equation treatment model (Specifications 4 and 5) for the impact of *Investment Grade {1 Rating}* and *Investment Grade {2 and 3 Ratings}* on the level of IPO underpricing for a sample of 4,251 U.S. IPOs from January 1997 to December 2016. Because of missing values, the actual number of observations is below 4,251. The main independent variables are the dummy indicators *Investment Grade {1 Rating}* and *Investment Grade {2 and 3 Ratings}*, which take a value of 1 if the firm has obtained a credit rating at investment grade and possesses either single or multiple ratings, 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 variables are defined in Appendix A. *, **, *** indicate two-tailed statistical significance at the 10%, 5% and 1% levels, respectively. Numbers in parentheses report standard errors. Industry and year fixed effects were taken into account in all specifications.

Panel B: Effect of Investment Grade on IPO Underpricing for Firms With Either Single or Multiple Ratings

	OLS	**Heckman**		**MLE**	
		Selection	**Outcome**	**Selection**	**Outcome**
VARIABLE	-1	-2	-3	-4	-5
Investment Grade {1 Rating}	-8.20		-9.78		-9.37
	(7.24)		(7.67)		(7.66)
Investment Grade {2 and 3 Ratings}	-16.85***		-19.81***		-19.63***
	(6.32)		(7.54)		(7.42)
Overhang	0.53***		0.48***		0.48***
	(0.07)		(0.08)		(0.08)
Underwriter	4.70***		7.02***		6.91***
	(1.51)		(1.68)		(1.68)
Auditor Rep.	2.93*		2.44		2.54
	(1.68)		(1.97)		(1.97)
Prim. Shares	2.38		3.52**		3.43**
	(1.60)		(1.77)		(1.76)
Revisions	1.04***		1.05***		1.05***
	(0.05)		(0.06)		(0.06)
Timelag	-0.02***		-0.02***		-0.02***
	(0.01)		(0.01)		(0.01)
Dotcom Period	37.01***		38.13***		38.02***
	(1.84)		(2.02)		(2.02)
Constant	9.13***	2.01***	9.38***	2.00***	8.30***
	(2.03)	(0.12)	(2.62)	(0.12)	(2.33)
Industry Fraction		-2.76***		-2.79***	
		(0.83)		(0.85)	
Profit		0.02		0.02	
		(0.02)		(0.02)	
Aged		0.31***		0.31***	
		(0.11)		(0.11)	
Leverage		0.28***		0.28**	
		(0.12)		(0.12)	
Inverse Mills Ratio		-25.26			
		(31.26)			
Year Fixed Effects	Y	N	N	N	N
Industry Fixed Effects	Y	N	N	N	N
N	3,817	3,184	3,184	3,184	3,184
Adjusted-R^2	0.24	-	-	-	-

Table 10: Endogeneity Control – Propensity Score Matching

This table illustrates the average treatment effect of the treated (ATET) for IPO initial returns in companies with *Multiple Ratings* versus those with *No Ratings* (Specification 2; for *Single Rating* firms versus those with *No Ratings*, see Specification 1), controlling for the endogeneity of multiple credit ratings (also single credit ratings) using propensity score matching. The sample consists of 4,251 IPOs from 1997 to 2016 in the U.S. stock market. Because of missing values, the actual number of observations is below 4,251. *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*, calculated as the percentage change between the first-day closing price and offer price. The variables used for matching are *Overhang*, *Underwriter Reputation*, *Auditor Reputation*, *Primary Shares*, *Log Proceeds (Size)*, *Log Age*, *Timelag*, *Internet Firm*, and *Filling Price Revisions*. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A. The maximum caliper width is set to 0.01.

	Initial Return -1		**Initial Return** -2
ATET		ATET	
(Single Rating vs No Rating)	-7.64***	(Multiple Ratings vs No Rating)	-11.77***
	(-2.48)		(-3.53)
Number of Observations	3,621		3,621

Table 11: Instrumental Variable Analysis on the Relationship Between Dodd–Frank Act and Underpricing

This table reports the results obtained from our IV analysis of the effect of multiple credit ratings (MCR) and a single credit rating (SCR) on IPO underpricing for a sample of 4,251 U.S. IPOs from January 1997 to December 2016. Because of missing values, the actual number of observations is below 4,251. In the first-stage regression, we examine the probability of a firm possessing multiple ratings (MCR - see Specification 1) or just a single one (SCR - see Specification 3), using a Dodd–Frank Act binary indicator, which is assigned a value of 1 after the 2010 period and 0 otherwise, as our instrumental variable. In addition, we include control variables, that is, *Tangibility*, *Log Sales*, *Growth*, *Profit*, *Aged* and *Leverage* (see Specifications 1 and 3). In the second-stage regression the main explanatory variable is *Predicted(Rating)*, obtained from the first-stage-regression. In Specifications 2 and 4, the dependent variable is the level of IPO underpricing. Standard errors are reported in parentheses below the coefficient estimates. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Industry and year fixed effects were taken into account in all specifications. All variables are defined in Appendix A.

	First-stage MCR Existence	**Second-stage Underpricing**	**First-stage SCR Existence**	**Second-stage Underpricing**
VARIABLE	-1	-2	-3	-4
Dodd–Frank	-0.12***		-0.13**	
	(0.04)		(0.06)	
Tangibility	0.31**		0.24*	
	(0.14)		(0.12)	
Log Sales	0.29***		0.18***	
	(0.02)		(0.02)	
Growth	-0.02		-0.02	
	(0.02)		(0.02)	
Profit	-0.01		-0.01	
	(0.01)		(0.01)	
Aged	0.30*		0.12	
	(0.16)		(0.11)	
Leverage	0.09**		0.03	
	(0.04)		(0.02)	
Constant	-3.61***	7.33***	-2.69***	-6.84
	(0.22)	(2.65)	(0.15)	(4.49)
Predicted (Rating)		-0.79***		-0.58***
		(0.28)		(0.22)
Overhang		0.48***		0.48***
		(0.09)		(0.09)
Underwriter		5.93***		7.33***
		(3.17)		(1.89)
Auditor Rep.		2.76		3.48
		(2.25)		(2.25)
Prim. Shares		3.58*		2.04
		(1.94)		(1.97)
Revisions		1.07***		1.07***
		(0.06)		(0.07)
Timelag		-0.03**		-0.03**
		(0.01)		(0.01)
Internet Firm		9.45***		8.29***
		(2.95)		(2.95)
Dotcom Period		38.81***		37.22***
		(2.33)		(2.35)
Durbin–Wu–Hausman Test Against H_0: *Variables Are Exogenous (p-value)*	0.01		0.06	
Year Fixed Effect	Y	Y	Y	Y
Industry Fixed Effect	Y	Y	Y	Y
F-statistic	180.02		165.36	
N	2,573	2,429	2,573	2,429
Adjusted-R^2	0.45	0.28	0.08	0.28

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