Institutional Pre-Commitment and Price Discovery in Lottery vs. Pro-rata IPO Auctions

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Abstract

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This study examines how institutional pre-commitment affects price discovery in IPO auctions, differentiating between randomly and proportionally assigned shares. We find that the issue price deviates less from the filing price when institutions pre-commit to purchasing shares, with a more pronounced effect under proportional assignment. This suggests that institutional pre-commitment promotes price discovery. However, the sensitivity to pre-commitment and issue price updates differs markedly between the two auction types. In proportionally assigned shares, price volatility decreases with pre-commitment and increases with issue-price updates, supporting the view that information asymmetry is the dominant driver of price volatility. In contrast, in randomly assigned shares, price volatility remains unchanged, suggesting that investor trading behavior is likely the main driver. These findings, which are robust to coefficient interpretation, underscore the importance of accurate filing prices and non-random, unbiased share allocation for price stability in the auction market.

JEL classification: G14, G15, G24, G28

Keywords: Lottery IPOs, pro-rata IPOs, institutional investors, issue-price, filing-price, price volatility, price discovery, beta regression, coefficient interpretation.

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1. Introduction

The auction method of initial public offering (IPO) has attracted much interest from scholars, practitioners, and policymakers worldwide. Unlike the U.S.-type book-building IPOs in which newly issued shares are primarily allocated to institutional investors at the discretion of the underwriting investment bank, open-bid, or transparent, auction IPOs—popular in emerging economies such as China and India—ensure that shares are allocated without bias to both retail and institutional investors (Firla-Cuchra and Jenkison, 2016, Anagol et al. 2018; Petkevich and Samdani, 2022). While book-building is often praised for its information production attributes—providing the underwriter with the tools necessary for incentivizing well-informed institutional investors (Benveniste and Spindt, 1989; Benveniste and Wilhlem, 1990; Sherman and Titman, 2002), the open-bid auction method with unbiased share allocation is lauded for its investor protection attributes—limiting the underwriter's ability to collude with investors to the detriment of the issuing firm (Biais et al., 2002; Biais and Faugeron-Crouzet, 2002).

Cognizant of the tradeoffs between issue methods—book-building trades off investor protection against information production, while auction prioritizes investor protection at the potential expense of information production—the Securities and Exchange Board of India (SEBI) revised the Disclosure and Investor Protection (DIP) guidelines regarding the allocation of IPO shares in July 2009. The revised guidelines aim to combine the information production attributes of book-building with the investor protection benefits of open-bid auction. The resulting "hybrid" IPO method allows the underwriter to commit a portion of the institutional tranche to "anchor" institutional investors at his discretion, as in book-building, and the remainder to non-anchor investors without discretion, as in the open-bid auction (Anagol et al. 2018; Lu and Samdani, 2019; Samdani, 2019; Petkevich and Samdani, 2022).

Whereas anchor institutional investors place their bids prior to the initial filing of the price-range, non-anchor institutional and retail investors bid after the filing. The allocation quotas to investor types are predetermined: 35% to retail investors, 15% to high-net-worth investors, and 50% to institutional investors (with 30% of institutional tranche reserved for anchor institutional investors if participating). If the IPO is oversubscribed and the underwriter is unable to allocate shares to all bidders, shares are assigned randomly using a lottery method; otherwise, assignment of shares is proportional, or on a pro-rata basis. While pro-rata based allocation ensures all bidders receive shares, lottery allocation does not guarantee this.

Anagol et al. (2018) and Petkevich and Samdani (2022) document interesting investor behavior in lottery IPOs that affects both their valuation of the IPO and their trading behavior. Anagol et al. (2018) identify an endowment effect whereby the winners of lottery IPOs value the shares more highly than the losers, leading winners to hold on to their shares longer than they would if the shares were allocated proportionally. Petkevich and Samdani (2022) show that in a sequential game between promoters and institutional investors, the latter's utility for underpricing is higher when shares are randomly assigned compared to when they are proportionally assigned. Both studies reveal that investors trade differently when shares are randomly assigned versus proportionally assigned, influencing trading in the secondary market.

Despite the attention placed on the roles of investors, both institutional and retail, underwriter discretion, and allocation criteria, several questions remain unanswered regarding the impact of institutional commitment prior to public filing on price discovery in the auction IPO market broadly and the lottery and pro-rata IPO markets specifically. We ask: Does institutional pre-commitment affect price discovery in auction IPOs? In auction IPOs with institutional pre-commitment, does the allocation criterion (lottery vs. pro-rata) influence price discovery?

Empirically, is the difference between the issue-price and filing-price in auction IPOs in which institutions pre-commit a measure of information production akin to what is observed in the U.S.-type book-building IPOs (Hanley, 1993)? How does price volatility in the secondary market respond to price update, or the deviation of issue-price form the filing -price, in scenarios where institutions pre-commit and allocation is random versus proportional?

The answers to the above questions are relevant for policymakers responsible for designing policies aimed at easing the IPO process and instilling investor confidence in the capital market. Such policies include measures to promote price discovery and stability in the capital market. The Jumpstart Our Business Startup (JOBS) Act enacted in April 2012 in the U.S., for instance, aims to revitalize the IPO market, which experienced a decline in the number of firms going public between 1999 and 2011. The JOBS Act essentially eases the IPO process by exempting firms from the internal audit controls stipulated by the Sarbanes-Oxley Act of 2002 and mitigates IPO process risk by allowing firms to "test the waters" prior to public filing (Doidge et al., 2013). Dambra et al. (2015) find that more companies chose the JOBS Act for its de-risking provision than for its burden-easing provision. Given the important role that institutional investors play in the IPO process, analyzing how their commitment to the IPO before public filing affects risk and uncertainty is essential for both the de-risking and the burden easing provisions in regulatory policies.

The results, based on a dataset of 226 auction IPOs in India from July 2009 to March 2019 (anchor investments did not exist in India prior to July 2009), reveal that the IPO issue-price deviates less from the filing-price when institutions pre-commit, with a more pronounced effect under proportional assignment. This finding is aligned with the view that favorable allocation of shares incentivizes anchor institutional investors to produce information, as argued by Benveniste and Spindt (1989), Benveniste and Wilhlem (1990), and Sherman and Titman (2002). The finding also supports the view that non-anchor institutional investors are always better off revealing their true valuation of the IPO, as revealed by Petkevich and Samdani (2022) in their study on non-anchor institutional investors' trading behavior when shares are randomly assigned versus when they are proportionally assigned.

However, the results regarding the sensitivity of price volatility to institutional pre-commitment and issue price updates differ markedly between the two auction types. In proportionally assigned shares, price volatility decreases with pre-commitment and increases with issue-price updates. In contrast, in randomly assigned shares, price volatility remains unchanged. Given that price volatility in IPOs in India is sensitive to uncertainty and information asymmetry (Francis et al., 2005; Rajgopal and Venkatachalam, 2011; Samdani, 2019), the positive relation between price volatility and issue-price update in pro-rata IPOs suggests that less information was revealed by anchor investors prior to the filing price and that market demand information was mostly revealed in bids by non-anchor investors. In contrast, the lack of statistical significance in IPO lotteries suggests that factors other than institutional pre-commitment and price updates influence price volatility. This result supports the view that price volatility in lottery IPOs is influenced by investors' strategic bidding and trading behavior (Anagol et al., 2018; Petkevich and Samdani, 2022).

The distinction between pro-rata IPOs and lottery IPOs underscores a fundamental difference in how price discovery and price stability are influenced in these two types of auctions. In pro-rata IPOs, secondary market trading is shaped by information produced by both anchor and non-anchor investors, whereas in lottery IPOs, trading is driven by investors' trading behavior. Price volatility in pro-rata auctions is predominantly affected by market uncertainties and information asymmetries, whereas in lottery auctions, they are primarily influenced by investors' trading strategies. The finding highlight how different IPO processes impact price volatility and stability, providing valuable insights for investors, issuers, and regulators, and enabling these stakeholders to make more informed and strategic decisions.

Finally, the study underscores the importance of appropriate model specification for ensuring the reliability of empirical findings. Specifically, our analysis uses beta regression to examine the factors influencing price volatility and issue-price update in auction IPOs. Both price volatility and issue-price update in our data sample are beta distributed, meaning they are continuous and bounded between 0 and 1. Our approach is motivated by recent studies, such as by Jennings et al. (2023) and Cohn et al. (2022), which highlight the risk measurement error poses to causal inferences in empirical research. We recognize that correct model specification, tailored to the data type at hand, is crucial for more accurate parameter estimation and meaningful interpretation. Linear regressions, such as ordinary least squares (OLS), and transformed linear regressions, such as log transformations, assume a constant relationship across the range of dependent variable values and require that residuals are normally distributed and homoscedastic (constant variance). In linear regression, coefficients represent the average effect of a one-unit change in the independent variable on the dependent variable, assuming all other variables are held constant. However, if the assumptions mentioned above are violated, these interpretations can become problematic or misleading (Cohn et al., 2022).

Transformations (like log transformation) attempt to fit models where relationships between variables are non-linear or where variance is not constant, but they can introduce their own interpretive challenges and do not always resolve underlying issues such as non-normality or outliers (Cohn et al., 2022). Unlike linear regression, beta regression can model the variance of the dependent variable as a function of the mean. This is especially useful when dealing with data that are continuous and bounded, providing more accurate interpretations of coefficients that are tailored to the nature of the data.

Indeed, increasing the sample size can improve the estimator's properties, such as consistency and efficiency, while using robust standard errors can help control for heteroscedasticity (non-constant variance). However, these methods do not address all types of model limitations, such as those arising from the fundamental nature of the data or its distribution, or the interpretation of coefficients. This is where beta regression can be particularly advantageous.

2. Institutional background and Hypotheses Development

2.1. Institutional background

The process of listing auction IPO shares on the stock exchanges in India begins with the issuer selecting a lead underwriter, a registrar, and a syndicate of investment banks to underwrite the IPO. The lead underwriter prepares a draft prospectus without providing information on either the filing-price range or the issue-price. After preparing the draft prospectus, the lead underwriter files the prospectus with the Securities and Exchange Board of India (SEBI). The prospectus is also distributed to banks in the syndicate group who, in turn, distribute the prospectus to investors. Following the distribution of the draft prospectus, the issuing firm embarks on a “road show” advertisement campaign to gather market-demand information and to determine the initial price range. Following this information-gathering period, the underwriter prepares a formal prospectus, which includes the filing-price range but not the issue-price. The underwriter then files the prospectus with the Registrar of Companies (ROC), which is 21 days after the draft prospectus is filed with the SEBI.

The allocation quotas for different investor types in India are fixed and pre-determined by the SEBI. More specifically, 50% of shares are reserved for institutional investors, 35% for retail investors with bids up to INR100,000 (around US$2,000), and 15% for high-net-worth retail investors bidding over INR100,000. In undersubscribed IPOs, which are not observed in the 2009–19 data sample, the underwriter redistributes shares from the undersubscribed tranche to the oversubscribed one. The share price is determined by the underwriter post bidding. Shares are proportionally allocated if all bids can be met, even if partially. In heavily oversubscribed IPOs where accommodating all bidders is impossible, the underwriter randomly assigns shares within each investor category (Anagol et al., 2018). The SEBI asserts that this approach mitigates investor type bias, a concern highlighted in studies on discretionary book-building IPOs in the U.S. (Aggarwal et al., 2002), and non-discretionary auction-type IPOs in Taiwan (Chiang et al., 2010).

In July 2009, the SEBI amended the DIP guidelines allowing the underwriter to allocate up to 30% of the institutional quota, or up to 15% of the IPO, to anchor investors prior to public filing at his discretion. In 2014, the SEBI increased the anchor portion of institutional quota from 30% to 60%, which is 30% of the total IPO. Anchor investors are institutional investors who subscribe to the issue before the IPO.

Bidding for anchor investment begins one day before the IPO. Anchor investors who subscribe to the issue are guaranteed allotment. However, anchor shares are locked-in for 30 days from the day of the IPO. Whereas the anchor price is set prior to public filing and thereby, prior to the bidding phase, the issue-price is set after the bidding phase. The price at which the shares are allotted to anchor investors is the higher of the anchor price and the issue-price. The anchor price is visible to potential bidders prior to the bidding phase. The bidding phase is transparent in that bidders can electronically observe the status of all bids in the book on a half-hourly basis. Bidders can modify their bids before the issue-price is set by the underwriter. In this regard, bids in India are non-binding. Shares are allotted to investors at the issue-price, which cannot deviate from the lower and upper price bands of the filing-price range. Trading in the secondary market begins seven days after the formal document is filed with the ROC.

2.2 Hypotheses development

Jenkinson, Morrison and Wilhelm (2005) examine whether the underwriter's ability to elicit information from investors prior to the initial filing of the price range holds economic significance in Europe. Unlike the 1993 Securities Act in the U.S., which prohibits the underwriter from making any "offers" to investors prior to the filing of the price range, European securities laws allow the exchange of information between the underwriter and investors prior to initial filing. Interestingly, the filing-price in the U.S. is often revised (50% of the time), while it is rarely the case for European IPOs. Jenkinson, Morrison and Wilhelm (2005) develop a theoretical model to explain this stark empirical difference between IPO issue-prices in the U.S. and those in Europe. The model essentially relates the accuracy of the filing-price to the information acquired by the underwriter through his interactions with well-informed institutional investors prior to the initial filing of the price range.

Jenkinson, Morrison and Wilhelm (2005) argue that the filing-price in European IPOs is more accurate—meaning it closely matches the market price—primarily because information production in European IPOs predominantly occurs during the pre-filing period. As a result, underwriters of European IPOs seldom need to revise the filing-price range. Furthermore, the issue-price in European IPOs is likely to deviate less from the filing-price. In contrast, in US book-building IPOs, a significant amount of information production occurs during the bidding period in the post-filing-price stage. Consequently, the filing-price for U.S. IPOs is less accurate, and the issue-price is likely to deviate significantly from the filing-price unless it is revised. In the Jenkinson, Morrison and Wilhelm (2005) model, the frequency of filing-price revisions and the magnitude of the issue-price deviation from the filing-price reflect not only the information produced during the pre- and post-filing stages but also the information incorporated into the filing-price and the issue-price.

Drawing on Jenkinson, Morrison and Wilhelm (2005), we argue that in India, the underwriter's ability to solicit anchor institutional investors for information prior to the initial filing of the price range aids in price discovery. This implies that the IPO issue-price aligns more closely with the filing-price when institutional investors pre-commit to purchasing shares. This effect is especially pronounced when shares are proportionally assigned to all bidders, as opposed to when shares are randomly assigned to lottery winners. In the case of lottery IPOs, factors other than the private information, such as high demand, revealed in bids also likely influence the issue price set by the underwriter. Thus, we hypothesize:

H1: The issue-price of proportionally assigned IPO shares deviates less from the filing-price when institutions pledge to purchase shares prior to the filing of the price range, and more when they do not.

Both the Jenkinson, Morrison and Wilhelm (2005) model and the Benveniste and Spindt (1989) model predict that IPO price updates and revisions are more pronounced when information is predominantly produced *after* the filing-price range is set by the underwriter. Additionally, the Jenkinson, Morrison and Wilhelm (2005) model predicts that IPO price updates and revisions are less pronounced when information is mostly produced *prior* to the filing of the price range. The underlying premise of these models is that institutional investors are well-informed and that the underwriter incentivizes them to reveal information private to institutional investors with favorable allocations. This incentive mechanism implies that favorably allocating shares to well-informed institutional investors promotes information production, which subsequently diminishes uncertainty and information asymmetry surrounding the value of the IPO. As a result, the incentive mechanism effectively reduces price volatility in the secondary market.

In the context of Indian IPOs, Anagol et al. (2018) identify an endowment effect in IPO lotteries, wherein lottery winners tend to hold onto their shares longer than typical investors who receive shares through mechanisms that guarantee at least partial allocation, such as in pro-rata based auctions. This behavior suggests a psychological attachment to shares acquired through perceived luck, which influences investors' trading behavior in the secondary market. Complementing their study, Petkevich and Samdani (2022) show that institutional investors derive greater utility from underpricing in IPO lotteries compared to pro-rata based auction IPOs. Their study reveals that, in a sequential game between controlling shareholders and institutional investors, the IPO share price is the equilibrium outcome, which is predicated on their respective utilities. The variation in utilities underscores the influence of the IPO shares allocation mechanism—lottery vs pro-rata—on investors' trading strategy and behavior.

These insights collectively suggest that trading activities in the secondary market are shaped not only by the uncertainty and information asymmetry surrounding the value of the IPO, as indicated by foundational work from Jenkinson, Morrison and Wilhelm (2005) and Benveniste and Spindt (1989), but also by the trading behaviors of investors, as highlighted in the studies by Anagol et al. (2018) and Petkevich and Samdani (2022). These behaviors are further influenced by the IPO's share allocation method, whether it be through a lottery or pro-rata system. Consequently, the choice of share allocation mechanism in auction IPOs stands out as a pivotal factor that can significantly influence market dynamics post-IPO.

The multifaceted relationship between allocation of IPO shares and post-IPO market dynamics underscores the importance of considering not just the economic uncertainties associated with the value of the IPO, but also the psychological and strategic behaviors of investors when analyzing their impact on market outcomes in auction IPO settings. The method of share allocation, by either random lottery or proportionate distribution, not only affects investor psychology and behavior but also shapes the overall market stability and efficiency following the IPO. This dual consideration of economic principles and investor psychology is crucial for a complete analysis of how various elements contribute to market dynamics in general and auction IPOs in particular.

Building on these insights, we posit that while institutional commitment to purchase shares prior to filing of the price range significantly reduces information asymmetry and subsequent price volatility in pro-rata IPOs, its impact is negligible in lottery IPOs. In the latter, the effects of institutional pre-commitment are likely crowded out by the dominant investor trading behaviors. The following hypothesis emerges from this line of reasoning:

H2: In auction IPOs, price volatility is lower when institutions pre-commit to purchasing shares and when shares are allocated on a pro-rata basis, as opposed to when allocation is random.

Acknowledging the significant role of price update in reflecting information produced, and considering the difference between information produced before versus after the filing-price, we contend that in lottery IPOs, updates to the issue-price—or its deviation from the initial filing-price—which typically reflects information produced post-filing-price compared to pre-filing-price range, have minimal to no impact on price volatility. This stance, which holds true even when institutions have pre-committed to the shares, is based on the assertion that the predominant factor influencing price volatility in lottery IPOs is the trading behavior of investors.

Conversely, in pro-rata based auction IPOs, we argue that price volatility increases with an increase in uncertainty and information asymmetry, as evidenced by the substantial deviation in issue price from the filing price in IPOs characterized by high price volatility. This pattern is particularly pronounced when institutional investors have pre-committed to the shares and the information produced is either insufficient or not adequately reflected in the filing price. In these pro-rata based auction scenarios, price updates are a critical factor influencing market stability, as they reflect the ongoing valuation updates of the IPO, which are heavily influenced by institutional actions. Based on these insights, we propose the following hypotheses:

H3: In auction IPOs, particularly those involving pro-rata allocation and pre-commitment by institutional investors, price volatility is positively related to issue-price update.

H4: In lottery IPOs, price volatility is unaffected by issue-price update, regardless of institutional investors' commitment prior to the filing of the price range.

3. Empirical strategy

Recognizing the threat measurement error and heteroskedasticity pose to causal inferences in empirical research (Jennings et al., 2023; Cohn et al., 2022), and acknowledging that these threats arise from model misspecification, we have deliberately chosen a regression model that best fits our data type. Our model selection approach specifically considers empirical features of the data, such as bounded support, skewed distribution, and heteroskedasticity, which can emerge when the model is not correctly specified.

Bounded support means the data is constrained within a specific range, such as 0 to 1. This constraint poses a problem because traditional regression models, like linear regression, can predict values outside this range, leading to unrealistic and invalid results. Skewed distribution refers to data that is not symmetrically distributed, often with a longer tail on one side. This can distort the analysis and affect the accuracy of parameter estimates in models that assume normality. Heteroskedasticity indicates that the variability of the data changes across the range of values. This poses a problem because it violates the assumption of constant variance in traditional regression models, leading to inefficient and biased estimates, thereby questioning the causal relationship predicted by the model.

To address these issues of bounded support, skewed distribution, and heteroskedasticity, we employ beta regression, which effectively models both conditional means and conditional dispersions. The conditional mean refers to the central tendency, or the expected value of the dependent variable given the independent variables, while the conditional dispersion refers to the variability or spread of the dependent variable around its mean, given the independent variables. By considering both the average outcome and the variability of outcomes, beta regression ensures a more accurate and reliable understanding of the data, thereby strengthening the validity of our causal inferences.

In contrast, linear regressions primarily focus on modeling the conditional mean and do not account for varying dispersion across the data range. This distinction is important because understanding both the central tendency and the variability of the data is crucial, especially when dealing with bounded, skewed, or heteroskedastic data. By only focusing on the conditional mean, linear regressions may miss important aspects of the data's distribution and variability, leading to incomplete or misleading conclusions (Gambetti et al., 2019). Two distributions with the same means but different shapes can have different sensitivities. Krüger and Rösch (2017) show that the probability of extreme losses is higher for loans that exhibit a beta distribution in their losses than a uniform distribution, even though the means of the two loss distributions are the same.

Given that our dependent variables—price volatility and issue-price update—are continuous and bounded between 0 and 1, beta regression emerges as the most logical choice for our analysis. This model allows us to address the specific features of our data type, ensuring a more accurate and insightful analysis of the factors influencing these variables.

In a correctly specified regression model, the residuals (i.e., the differences between the observed and predicted values) are expected to be distributed randomly around zero. This property, known as homoskedasticity, implies a constant variance in the residuals. If the residuals are evenly spread around a mean of zero (i.e., the residuals are distributed randomly around zero, or the residuals have symmetric distribution with constant variance), the model is considered to be doing a good job of predicting the average value of the dependent variable, given the independents. If there is a pattern in the residuals (e.g., they spread out more for larger fitted values), it might indicate heteroskedasticity, which violates the constant variance assumption and can lead to inefficient and potentially biased estimates.

The above principles and conditions concerning the behavior of residuals in a correctly specified regression model holds true in the context of OLS regression models, which are often used in analyses where the dependent variable is continuous and unbounded. For these models, diagnostic tools such as residual plots and tests for homoskedasticity are useful for ensuring model validity. However, for models where the dependent variable is bounded or follows a different distribution (like beta distribution), other diagnostic tools and considerations are necessary. For beta distributed data, the half-normal probability plot with a simulated envelope is a useful diagnostic tool for examining the adequacy of the fitted model (Neter et al., 1989; Ferrari and Cribari-Neto, 2004). The simulated envelope effectively highlights the extreme values (Atkinson, 1981). For example, when using 19 simulations, the probability of the absolute residual falling outside of the simulated envelope is 5 percent (1/20). Large deviations of points from the mean of the simulated values, or occurrence of points outside the simulated envelope, are indications that the fitted model is not appropriate. Cases in which the absolute deviance residuals fall outside of the simulated envelope limits are therefore worthy of additional investigation. It is important to note that the half-normal probability plot of the absolute residuals may not necessarily provide straight line even when the fitted model is correct (Ferrari and Cribari-Neto, 2004; Neter et al., 1989).

We recognize that a large sample size can increase the power of statistical tests, making it more likely to detect statistically significant effects even when the data deviates from normality or other assumptions. Furthermore, the use of robust standard errors can improve the reliability of hypothesis tests in the presence of heteroscedasticity or other violations of classical assumptions—robust standard errors help account for potential issues related to the distribution of residuals. Even though beta-distributed data is not normally distributed, in certain circumstances and with a sufficiently large sample size, the Central Limit Theorem suggests that the distribution of sample means can approximate normality. If there are outliers in the data, robust standard errors can help mitigate their impact, potentially leading to statistically significant results. While these factors contribute to obtaining statistically significant results with linear regressions, it is important to note that, as pointed out by Cohn et al. (2022), the interpretation of coefficients may not be as straightforward or meaningful when using linear regression, such as OLS, and transformed linear regressions, such as log or Box-Cox transformations, with bounded distributed data. Linear regressions assume that the dependent variable can take on any value, but this assumption is violated with bounded data. Moreover, bounded data often exhibit heteroskedasticity, where the variance of the errors changes across the range of values, and non-normal error distributions. These violations of linear regression model assumptions result in inefficient and biased estimates. Consequently, OLS and Box-Cox coefficients might not correctly reflect the nature or strength of the relationships in the data.

We also acknowledge that endogeneity is a significant concern in empirical finance research, often arising from omitted variables, measurement error, or reverse causality. To address the issue of endogeneity due to omitted variables, we include several control variables in our models. These controls help to isolate the effect of institutional pre-commitment on IPO outcomes by accounting for other factors that could influence the dependent variables. However, including control variables alone does not fully eliminate the concern of endogeneity, as it may not address issues related to measurement error or reverse causality.

Endogeneity due to reverse causality is less likely in our context because institutional pre-commitment decisions are made well in advance of trading in the secondary market. When firms decide to engage institutional investors early in the IPO process and institutional investors decide to pre-commit to purchasing shares, these decisions occur before the firm sets its initial price range and long before the shares begin trading. Given the timing, it is highly improbable that firms can accurately anticipate future price volatility and adjust their pre-commitment strategies accordingly.

Furthermore, economic theory does not support a causal relationship where price volatility influences a firm's decision to solicit institutional investors prior to the filing of the price range. Instead, the theoretical framework suggests that the participation of institutional investors in the IPO process should impact market outcomes, including price volatility. It is well-documented that institutional investors bring more information and stability to the market due to their sophisticated analysis and large-scale investments, which can reduce uncertainty and price volatility.

In contrast, it is not theoretically plausible that the firm's anticipated price volatility would drive the decision to seek institutional pre-commitment. The firm's primary motivation for securing institutional investors early is to enhance the credibility and attractiveness of the IPO, not to react to speculative price volatility. Therefore, our theoretical and empirical framework supports the notion that institutional pre-commitment influences price volatility, rather than price volatility driving institutional pre-commitment.

4. Data

The IPO data sample is collected from Prime Database, Chittorgarh, the Bombay Stock Exchange (BSE), and the National Stock Exchange (NSE) in India. The market data is collected from Money Control. The data sample consists of 226 auction IPOs in the July 2009–March 19 period in India. The descriptive statistics are shown in Table 1.

[Insert Table 1]

From the descriptive statistics in Table 1, Panel A, we observe that the means of some independent variables, specifically, issue amount, institutional demand, and retail demand, are larger than the medians, indicating potential skewness in these explanatory variables. The table also shows a large range of values for the independent variables. For instance, the values of institutional demand vary from 0.03 to 143.62. Furthermore, the associated ratio of the maximum value (143.62) to the minimum value (0.03) of institutional demand, which is 4787, exceeds 100. Following the guidance of Cook and Weisberg (2009), we transform the independent variables using the logarithm transformation method, and present the summarized results in Panel B. The mean and the median of the transformed independent variables, issue amount, institutional demand, and retail demand as shown in Panel B, are closely aligned, which indicates the effectiveness of the logarithm transformation.

To offer a more tangible illustration of the variability in independent variables, Figure 1 presents boxplots of those independent variables that initially displayed pronounced variability.

[Insert Figure 1]

The primary benefit of logarithm transformation, as evidenced by the graphical representation in Figure 1, is that it makes the distribution of the independent variables less skewed and more symmetrical. By compressing the spread of the larger values, the transformation ensures the overall data distribution leans towards symmetry. Such a transformation is very useful, especially for statistical techniques that presuppose a normal data distribution.

Next, we examine the correlations between the variables used in the analysis. The Pearson's correlation matrix is shown in Table 2.

[Insert Table 2]

The correlation coefficients reported in Column 1 of Table 2 reveal a correlation between price volatility and various IPO characteristics, such as issue-price update, underpricing, issue amount, institutional demand, retail demand, earning-per-share (EPS), and controlling shareholders' retained equity. Column 2 of Table 2 indicates a correlation between issue-price update and factors like issue amount, institutional demand, and controlling shareholders' retained equity. These correlations suggest the importance of controlling for firm-specific characteristics in the analysis. Complete definitions of these variables are found in Appendix A.

Next, we present the descriptive statistics of the dependent variables and the independent variables categorized by lottery pre-commitment, pro-rata pre-commitment, and year. Lottery pre-commitment includes IPOs with randomly assigned shares and pre-commitment from anchor institutional investors. Pro-rata pre-commitment includes IPOs with shares assigned on a pro-rata basis and pre-commitment from anchor institutional investors. These statistics are detailed in Tables 3 and 4.

[Insert Table 3]

[Insert Table 4]

The summary statistics presented in Table 3 reveal that the mean and median values of issue-price update in lottery IPOs are relatively lower with institutional pre-commitment (43 IPOs) compared to without (14 IPOs). This observation aligns with the prediction of Hypothesis H1. The table also shows that the mean, median, and standard deviation of both price volatility and issue-price update in pro-rata IPOs are relatively lower with institutional pre-commitment (95 IPOs) compared to without (74 IPOs). This observation aligns with the predictions of H1 and H2. Conversely, the mean, median, and standard deviation values of price volatility in lottery IPOs are similar with institutional pre-commitment compared to without, which also aligns with the predictions of H2.

Table 4 indicates that IPO characteristics in the data sample are not homogenous across years. Specifically, the table shows that the mean, median, and SD of IPO characteristics are not homogenous across years. This suggests the importance of controlling for year fixed-effects.

Boxplots are powerful tools for visually summarizing data. They provide a quick glance at the distribution of the dataset, highlighting its central tendency, variability, and skewness. The median, a key feature of the boxplot, is indicated by the line that divides the box into two parts. This line represents the middle value of the data set, with half of the data points lying above this value and the other half below.

In a boxplot, the box itself represents the interquartile range (IQR), which encompasses the middle 50% of the dataset. This range spans from the 25th percentile (the lower quartile, Q1) to the 75th percentile (the upper quartile, Q3). The line inside the box marks the median (50th percentile, Q2) of the dataset. When the median is approximately in the center of the box, it suggests that the data within the IQR is symmetrically distributed around the median. This means the distances between the median and the quartiles (Q1 and Q3) are roughly equal, implying a relatively symmetrical distribution of the middle 50% of the data. If the median is closer to the bottom of the box (near Q1), it indicates a positive skew. In this case, the lower half of the middle 50% of the data (from Q1 to Q2) is more compressed than the upper half (from Q2 to Q3), and there is a longer tail extending towards higher values beyond Q3. If the median is closer to the top of the box (near Q3), it indicates a negative skew. Here, the upper half of the middle 50% of the data (from Q2 to Q3) is more compressed than the lower half (from Q1 to Q2), and there is a longer tail extending towards lower values below Q1. Thus, the position of the median within the box helps indicate the skewness of the distribution by showing whether the data within the IQR is evenly distributed around the median or not.

In our case, the boxplots for Table 3 and Table 4, as shown in Figure 2 and Figure 3, respectively, provide a visual representation of these aspects of the datasets. By examining these boxplots, we can quickly assess the central tendency, spread, and skewness of the data in each table.

[Insert Figure 2]

[Insert Figure 3]

The boxplots in Figure 2 effectively illustrate the differences in price volatility and issue-price updates between lottery IPOs and pro-rata IPOs. The key observations from the boxplots are as follows: The median lines for issue-price update and price volatility in the boxplots of pro-rata IPOs are lower when institutions pre-commit compared to when they do not. The median lines are also near the middle of the box, suggesting that the data is symmetrically distributed. While the median line for issue-price update in lottery IPOs is lower when institutions pre-commit compared to when they do not, similar to the observation for pro-rata IPOs, the median line for price volatility is lower when institutions pre-commit compared to when they do not. Importantly, the boxplot also shows that the median line is close to Q1, suggesting a positive skew and thereby justifying the use of beta regression models in the analysis.

The boxplots in Figure 3 compare the medians of price volatility and issue-price updates across years. The figure shows that the medians vary across years, suggesting the need to control for year fixed effects in the regressions, in addition to industry fixed effects. Fixed effects, common features in econometric and statistical models, are utilized to control for variations across different industries and years within the economy. They specifically aim to account for characteristics that are either unobservable or unmeasured within each industry or year. By including these fixed effects in the regression models, the analysis effectively eliminates variations attributable to industry-specific and year-specific factors. This allows for a more concentrated focus on the impact of the independent variables of interest, thereby enhancing the accuracy and reliability of the regression results. Figure 3 also shows that the median lines for issue-price update and price volatility are not in the middle of the box for some years, indicating skewness in the data. This underscores the importance of appropriate model specification for accurate parameter estimation.

The next step prior to fitting the regression models is to define the dependent variables: price volatility and issue-price update. Taking cues from Mangiafico (2016), who defines the dependent variable as a *function* of student sodium intake, and Cribari-Neto and Zeileis (2010), who define the dependent variable as a *function* of reading accuracy, we define price volatility as a *function* of daily price change over a thirty-day period starting from the second day of trading (the first-day of trading is excluded as it used to determine IPO underpricing). The average daily price volatility over a thirty-day period in our data sample is, not surprisingly, continuous and bounded between 0 and 1. We define issue-price update as a function of the absolute value of issue-price and the midpoint of the initial price range, where the filing-price range is the price range set by the underwriter prior to the bidding phase and the issue-price is the price at which IPO shares are distributed to investors in the primary market. SEBI guidelines stipulate that the upper bound of the filing-price range cannot exceed the lower bound by more than 20%, and the issue-price must fall within the lower and upper bounds of the filing-price range. Owing to these constraints and the function design, the issue-price update variable in the data sample is also continuous and bounded between 0 and 1. Consequently, the standard beta distribution is the logical choice for modeling this type of data distribution. The histogram with the density curve for price volatility and issue-price update are shown in Figure 4.

[Insert Figure 4]

The histogram overlaid with a density curve in Figure 4 illustrates that price volatility is confined within the standard interval of 0 to 1. Correspondingly, Table 1 shows that the mean and median of price volatility are closely aligned, indicating a symmetric distribution of the data. However, the skewness value of 1.53 for price volatility density shown in Figure 4 suggests a positive skew, characterized by the more pronounced right tail in the distribution. This type of skewness in the dependent variable, price volatility, could lead to skewed residuals in regression analysis, potentially challenging the assumptions of linearity and normality. Deviations from these assumptions can compromise the validity of statistical tests. Specifically, these deviations affect the reliability of findings by impacting the significance and magnitude of regression coefficients. Moreover, when the underlying assumptions of a model are not met, there can be a significant loss of efficiency, meaning that the estimates produced by the regression model are less precise (Cohn et al., 2022). This reduction in precision compromises the accuracy and interpretability of the results, potentially leading to less confident and suboptimal decision-making based on the analysis. The kurtosis value for price volatility shown in the figure, standing at 5.39, points to a leptokurtic distribution. This implies that the distribution has heavier tails and is more prone to extreme values compared to a normal distribution, which typically has a kurtosis of 3. High kurtosis could signal the presence of outliers or influential data points, warranting closer scrutiny in the analysis.

Figure 4 also illustrates that issue-price update values range between 0 and 1. With a skewness of 0.81 and a kurtosis of 3.03, the distribution of issue-price update is less skewed and approximates a normal distribution. These higher moments - skewness and kurtosis - are crucial for understanding the data's distribution. Such insights not only aid in determining the appropriate statistical analysis and modeling approach but also in tailoring model specifications to accurately reflect the underlying data characteristics. By recognizing and addressing these distributional properties, the analysis can be more accurately aligned with the data's inherent structure, enhancing the reliability and interpretability of the findings. This understanding is particularly important in linear regression analysis, where the assumption of normally distributed residuals is central to the validity of many statistical inferences. Therefore, acknowledging and accounting for these distribution characteristics in price volatility and issue-price update is crucial for robust and meaningful analysis in this context.

Next, we visually examine the relationships posited by our hypotheses using bar charts and scatter plots. The patterns are presented in Figure 5.

[Insert Figure 5]

The bar graphs on the top left and bottom left illustrate that issue-price update is notably lower when institutions pre-commit in both pro-rata and lottery IPOs. The statistically significant *p*-values (***) reinforce this observation, aligning well with the predictions of Hypothesis H1.

The middle bar graph in the top row of Figure 5 indicates that price volatility in lottery IPOs remains virtually unchanged regardless of whether institutions pre-commit. The accompanying *p*-value, which is not statistically significant, suggests that institutional commitment does not significantly impact return volatility in this context.

Conversely, the middle bar graph on the bottom row demonstrates that price volatility is reduced in pro-rata IPOs when institutions pre-commit, as opposed to when they do not. This outcome, supported by a statistically significant *p*-value (***), is consistent with Hypothesis H2.

Moreover, the scatter plots in Figure 5 offer further insights. The plot in the top row reveals that the issue-price update does not significantly influence price volatility in lottery IPOs, as indicated by the smooth curve that is upward sloping at first and then downward sloping, supporting H4. Meanwhile, the plot in the bottom row indicates a positive relationship between price update and price volatility in pro-rata IPOs, as shown by the mostly upward-sloping curve, corroborating H3.

Following this initial visual assessment, we conduct more detailed statistical tests to further explore how and whether the data supports the relationships predicted by our hypotheses, particularly focusing on conditions of pre-commitment in both pro-rata and lottery IPOs. To ensure the appropriateness of the statistical methods used, we first test the normality of these variables using the Shapiro-Wilk test, which was introduced by Shapiro and Wilk (1965) to detect non-normality. Razali and Wah (2011) compare several normality tests and find that the Shapiro-Wilk test is the most effective in detecting non-normality for various types of distributions and sample sizes, particularly for small sample sizes. Yap and Sim (2011) also provide a comprehensive review of normality tests and highlight the Shapiro-Wilk test as one of the most reliable tests available.

The Shapiro-Wilk test results (p-values shown in the bar charts in Figure 5), which specifically check whether a variable follows a normal distribution, indicate that the variables are not normally distributed. Consequently, to accurately analyze these non-normally distributed variables, we next employ the Mann-Whitney test. Unlike the Shapiro-Wilk test, which tests for normality, the Mann-Whitney test (Mann and Whitney, 1947) is used for comparing differences between two independent groups. It is more suitable for situations where the data does not meet the normality assumption, providing a robust method for detecting differences in central tendencies between groups.

It is important to note that these tests, while informative, are still preliminary in nature and primarily aimed at confirming the validity of the data for further analysis. They do not replace the need for comprehensive regression analysis. The sequence of analytical steps—from using visual tools for an initial overview to applying more thorough statistical tests—ensures a comprehensive evaluation of the data, setting the stage for more rigorous, subsequent analysis.

5. Analysis and results

We present our analysis and discuss the main results in two subsections. In the first subsection, we summarize the results of the analysis testing Hypotheses H1, derived from beta regressions, where the dependent variable, IPO issue-price update, is beta distributed. In the second subsection, we delineate the results of the analysis testing Hypotheses H2, H3, and H4, using beta regression, where the dependent variable, price volatility, also follows a beta distribution.

5.1 Is issue-price update in auction IPOs sensitive to institutional investors' pledge to purchase shares prior to the initial filing of the price range?

In this section, we investigate the relationship between IPO issue-price update—defined as the deviation in the issue-price from the filing-price range—and institutional commitment prior to the filing of the price range. We use the following specification for this examination:

$$
\begin{aligned}
&Issue\ Price\ Update \\
&= \beta_0 + \beta_1 Lottery\ pre\text{–}\ commitment\ + \beta_2\ Pro\text{–}\ rata\ Pre\text{–}\ commitment + \beta_3 Lottery\ IPO \\
&+\ Controls \\
&+ \varepsilon \qquad (1)
\end{aligned}
$$

We use beta regression with issue-price update as the dependent variable and lottery pre-commitment and pro-rata pre-commitment as the key independent variables. Lottery pre-commitment in Eq. (1) is a dummy variable that takes a value of 1 if the shares are randomly assigned to investors and institutions pre-commit to purchase shares prior to the filing of the price range, and zero otherwise. Pro-rata pre-commitment is a dummy variable that takes a value of 1 if the shares are assigned on a pro-rata basis and institutions pre-commit to purchase shares prior to the filing of the price range, and zero otherwise. Lottery IPO is a dummy variable that takes a value of 1 if the shares are randomly assigned and zero if they are proportionally assigned. The reference category is pro-rata IPOs with no pre-commitment from institutional investors. The regression results based on the specification in Eq. (1) are presented in Table 5.

[Insert Table 5]

The coefficients for pro-rata pre-commitment variables are negative and statistically significant in Models 1 through 6 in Table 5, supporting the predictions of H1. Interestingly, the coefficients for lottery pre-commitment are also negative and statistically significant, suggesting that uncertainty and information asymmetry also plays a role in lottery IPOs. In Models 7 and 8, we replace the key independent variables, lottery pre-commitment and pro-rata pre-commitment, by institutional demand and its interaction with pre-commitment to test whether the negative and statistically significant effects of lottery pre-commitment and pro-rata pre-commitment on issue-price update are due to institutional demand and not because of the allocation criteria (lottery vs pro-rata allocation with and without institutional pre-commitment). The regression equation used in Models 7 and 8 is as follows:

$$\begin{aligned} &Issue\ Price\ Update \\ &= \beta_0 + \beta_1 Insititutional\ Demand\ + \beta_2\, Pre\!-commitment \\ &+ \beta_3 Insitituional\ Demand \times Pre\!-commitment + \ Controls \\ &+ \varepsilon \end{aligned} \tag{2}$$

The main effect of institutional demand in Models 7 and 8 in Table 5 is negative and statistically significant, suggesting that institutional demand, which also indicates institutional interest in the IPO, promotes price discovery regardless of whether institutions pre-commit to purchasing shares. Similarly, the main effect of pre-commitment in these two models is negative and statistically significant, indicating that pre-commitment also promotes price discovery independently of institutional demand.

However, the coefficients of the interaction between institutional demand and pre-commitment are statistically not significant in both Model 7 and Model 8. A non-significant coefficient for this interaction term suggests that there is no evidence of a differential effect of institutional demand on issue-price update in IPOs in which institutional investors pre-commit to purchasing shares compared to IPOs in which they do not.

This lack of statistical significance further confirms the prediction of H1, indicating that the effect of pre-commitment on issue-price update in the two types of auctions is independent of institutional demand.

As in Ferrari and Cribari-Neto (2004) and Gambetti et al. (2019), the performance of models is compared in terms of Pseudo R-squared measures. Pseudo R-squared is a goodness-of-fit measure for regression models that, unlike the traditional R-squared used in ordinary least squares regression, is suitable for models where the dependent variable is not only continuous but alos bounded, such as beta regression models. It provides an indication of how well the model explains the variability of the dependent variable, albeit on a different scale.

Table 5 reveals a marked improvement in the explanatory power of the regression model, as indicated by the increase in the percentage of Pseudo R-squared from about 19% in Model 1 to about 40% in the extended multivariate Model 6. This significant increase suggests that the extended model, which includes additional variables, provides a much better fit to the data. The higher Pseudo R-squared value means that the extended model captures more of the variability in the issue-price update, thus offering a more comprehensive understanding of the factors influencing price adjustments in IPOs.

Furthermore, the precision parameters (φ) in the beta regressions show a sizable increase from 62.54 in Model 1 to 86.09 in Model 6. The precision parameter in beta regression is inversely related to the variance of the dependent variable; a higher precision parameter indicates lower variance. This increase implies that the variance of the issue-price update, which is a function of its mean and precision parameter, decreases as the precision parameter increases. Therefore, a higher precision parameter in Model 6 suggests that the model is more precise and consistent in predicting the issue-price update.

Such a trend indicates that the beta regression model is well-suited for capturing the variability in issue-price updates. The improved explanatory power and increased precision parameter underscore the robustness of the extended model in accounting for the factors influencing the issue-price update in IPOs, further validating the appropriateness of beta regression for the analysis.

To further evaluate the model's performance, we compare the estimators based on their root mean squared error (RMSE), which is the square root of the average squared coefficient estimation error. An estimator is a statistical method or formula used to make inferences about population parameters based on sample data. For example, the sample mean is an estimator of the population mean. In regression models, the coefficients estimated from the data are the estimators of the true relationship between the variables.

RMSE provides a common metric for comparing dynamic estimators, with lower RMSE values indicating more precise estimates. Thus, a smaller RMSE indicates a better estimator (Flannery and Hankins, 2013; Cohn et al., 2022). Model 6 in Table 5 has a relatively low RMSE (0.018) compared with Model 1 in Table 5, which has an RMSE of 0.020. Although the RMSEs differ slightly across all models in Table 5, they are all quite small. Overall, beta regression appears to be the appropriate choice.

Figure 6 shows the diagnostic plots of the residuals, which are useful for checking the fit of the multivariate full regression Model 6 in Table 5.

[Insert Figure 6]

The analysis of various residual plots in Figure 6 offers insights into the model fit and the data's characteristics. The top left residual plot reveals no apparent pattern, suggesting a good fit between the model and the data. The deviance residuals, as seen in the bottom right plot, center around zero, further indicating an adequate model fit. The half-normal plot of residuals, displayed in the bottom left, highlights a few observations deviating from the majority, which are closely clustered within the confidence bands of the simulated envelope. These majority values align well with the mean of the simulated values, as indicated by the dashed lines, implying effective performance of the beta model.

In the scatterplot of Cook's distance versus the number of observations, shown in the top right corner of Figure 6, all Cook's distance values are below 0.5. This suggests the absence of highly influential points in the dataset, reinforcing the reliability of the model (Cook and Weisberg, 2009).

5.2 Is price volatility in auction IPOs sensitive to issue-price update, allocation criterion (lottery vs. pro-rata) and institutional pre-commitment?

In this section, we examine whether price volatility in auction IPOs is affected by issue-price update, lottery pre-commitment, and pro-rata pre-commitment variables using the following specification:

$$
\begin{aligned}
&Price\ Volitility \\
&\quad = \beta_0 + \ \beta_1 Issue\ Price\ Update + \beta_2 Lottery\ Pre\text{–}\ commitment \\
&\quad + \beta_3 Pro\text{–}\ rata\ Pre\text{–}\ commitment \\
&\quad + \ \beta_4 Issue\ Price\ Update \times Lottery\ Pre\text{–}\ commitment \\
&\quad + \beta_5 Issue\ Price\ Update \times Pro\text{–}\ rata\ Pre\text{–}\ commitment \\
&\quad + \beta_6 Lottery\ IPO + Controls \\
&\quad + \varepsilon \qquad (3)
\end{aligned}
$$

We use a beta regression approach and fit the regression models based on the specification in Eq. (3). The regression results are reported in Table 6.

[Insert Table 6]

The reference category in Models 1 through 6 of Table 6 is pro-rata IPOs with no pre-commitment from institutional investors. The coefficients for the pro-rata pre-commitment variable across these six models are consistently negative and statistically significant, whereas the coefficients for the lottery pre-commitment variable are not statistically significant. These results support the predictions of Hypothesis H2.

Additionally, the table shows that the coefficients for the interaction term, issue-price update × pro-rata pre-commitment, in the first six models are consistently positive and statistically significant. In contrast, the coefficients for the interaction term, issue-price update × lottery pre-commitment, are not statistically significant. These findings indicate that price volatility in auction IPOs with pro-rata allocation of shares is sensitive to information asymmetry, as evidenced by the significant coefficients for the pro-rata pre-commitment variable and its interaction with the issue-price update.

Conversely, the lack of significant coefficients for the lottery pre-commitment variable and its interaction with issue price update suggests that price volatility in auction IPOs with random allocation of shares is less sensitive to information asymmetry and perhaps more influenced by investor trading behavior. These observations support the premises of Hypotheses H3 and H4.

In Models 7 through 14, the interaction terms, issue-price update × lottery pre-commitment and issue-price update × pro-rata pre-commitment, are omitted to address concerns that the statistical significance, or lack thereof, of some variables, such as issue-price update, may be influenced by multicollinearity. The coefficients for the issue-price update variable in these models remain not statistically significant even after excluding the allocation criteria (random, proportional, and biased) variables from the regression models, further supporting the premise of H4.

In Models 5 through 14, we control for the effect of amendments to the Disclosure and Investor Protection (DIP) guidelines effective January 2012 in India, which include restrictions on deviations from price bands conditional on issue size. This control is implemented by interacting the Post 2012 dummy with the Amount<2.5b dummy. Models 11 through 14 also include interaction terms between issue-price update, institutional demand, and pre-commitment to address the concern that the effect of allocation criteria (random, proportional, or biased) on price volatility could be due to institutional demand rather than the allocation criteria, as the two are highly correlated. The statistically not significant coefficients for the interaction terms institutional demand × pre-commitment, issue-price update × institutional demand, and issue-price update × institutional demand × pre-commitment indicate that it is not institutional demand but the allocation criterion (random, proportional, or biased) that affects the relationship between price volatility and issue-price update in auction IPOs, thereby supporting the predictions of H3 and H4.

As in Table 5, there is a significant increase in the percentage of Pseudo R-squared in Table 6, from 27% in Model 1 to about 60% in Model 6, indicating a marked improvement in the model's explanatory power. The precision parameters (φ) in the beta regressions also show a substantial increase from 191.20 in Model 1 to 365.79 in Model 6. This trend indicates that the beta regression model is well-suited for capturing the variability in price volatility, further validating the appropriateness of beta regression for the analysis. While the RMSEs differ slightly across all models in Table 6, they are all quite small, indicating that beta regression appears to be the appropriate approach for modeling this data type.

Figure 7 shows the diagnostic plots of the residuals for the full multivariate Model 6 in Table 6.

[Insert Figure 7]

The top left residual plot in Figure 7 shows no apparent pattern—the residuals are evenly spread around zero, suggesting a constant variance. Additionally, the median of deviance residuals (bottom right plot) is close to zero, indicating that the fit of the model with the data is appropriate. From the half-normal plot of the residuals (bottom left plot), it appears that only a few observations are separated and most of the absolute deviance residuals do not fall outside of the confidence bands provided by the simulated envelope. These values are close to the mean of the simulated values (dashed line), suggesting that the fitted model is suitable. The Cook's distance values from the scatterplot of Cook's distance versus the number of observations (top right plot) are less than 0.5, indicating that there is no highly influential point in the dataset.

6. Robustness checks

6.1 Zero-inflated beta regression

The beta regression method employed thus far assumes no observations equal to zero for the dependent variable. To meet this constraint, we excluded two observations of IPOs with an issue-price update equal to zero (where the issue-price equals the mid-point of the filing-price range). In a study examining the determinants of beta distributed bond recovery rates, Gambetti et al. (2019) use beta regression and exclude one observation from their data sample that has a value equal to 1. They justify this exclusion by explaining that the observation in question exhibits an outlier residual even after adjusting for the subtraction quantity used to ensure that all observations fall within the (0, 1) range. An outlier residual indicates that the data point deviates significantly from the predicted value of the model, suggesting that it does not fit well within the overall pattern of the data.

Furthermore, Gambetti et al. (2019) identify this particular observation as a leverage point. In statistical terms, a leverage point is an observation that has an undue influence on the estimation of the model parameters. Such points can disproportionately affect the model's results, leading to potentially misleading conclusions. By excluding this observation, Gambetti et al. (2019) aim to improve the robustness and accuracy of their beta regression model, ensuring that their findings more accurately reflect the underlying relationships in the data without being skewed by an anomalous data point.

We acknowledge that fitting the standard beta regression model to a data sample which includes observations with zero values may not be appropriate. For this reason, we exclude the two observations with zero values from the data sample. To test the sensitivity of our results in Specification 1 (Table 5) to IPOs with an issue price update equal to zero, we include the previously excluded observations with a zero value and fit the zero-inflated beta regression models, which not only include values within the unit interval (0, 1) but also an excess number of zeroes, according to the specification in Eq. (1). This is accomplished by combining two components: a beta distribution for the values within (0, 1) and a separate process for generating zeroes. This piecewise approach allows the model to handle both the continuous nature of the data within the interval and the discrete occurrence of zeroes.

According to Liu et al. (2015) and Kieschnick and McCullough (2003), zero-inflated beta regression provides a robust framework for analyzing data that includes an excess of zeroes, effectively addressing the limitations of standard beta regression models in such contexts. The model operates as follows: one part of the model estimates the probability that an observation is zero, and the other part uses the beta distribution to model the values within the (0, 1) range. This dual approach method offers several advantages. Firstly, it improves the fit of the model by correctly accounting for the excess zeroes, leading to more reliable parameter estimates. Secondly, it enhances the interpretability of the results by distinguishing between the processes generating the zeroes and those affecting the continuous data. Lastly, it allows researchers to identify factors that contribute specifically to the occurrence of zeroes. The results of zero-inflated beta regression are reported in Table B1 in Appendix B.

[Insert Table B1]

Table B1 shows that, consistent with the results reported for beta-regression in Table 5, the coefficients for pro-rata IPOs with institutional pre-commitment are statistically significant and negative across all zero-inflated beta models using the posterior confidence interval approach. This approach, which is primarily used in Bayesian analysis, treats parameters as random variables. Unlike classical statistics, Bayesian analysis aims to estimate the distribution of the parameters based on the observed data. The "posterior" refers to the distribution of these parameters after taking the observed data into account. This is in contrast to the "prior" distribution, which represents knowledge or assumptions about the parameters before observing the data. The posterior distribution reflects the current understanding, including uncertainties, about the parameters. In Bayesian terms, the confidence interval, often called the credible interval, is derived from this posterior distribution. For instance, a 95% confidence interval would encompass the range between the 2.5th and 97.5th percentiles of the posterior distribution. This interval provides a range of values for the parameter that are plausible given the observed data, making the Bayesian confidence interval more intuitively interpretable than its frequentist counterpart, offering a comprehensive view of the uncertainty and variability in parameter estimates, especially when integrating prior information into the analysis.

The analysis of the regression models in Table B1 also reveals that the coefficients for lottery IPOs with institutional pre-commitments prior to public filing are statistically significant and negative in two of the six models at 95% confidence level, whereas at 95% confidence level in Table 5 is statistically significant across all six models. This observation stands in contrast to the findings in Table 5, where the data excludes IPOs with an issue-price update of zero. This contrast underscores the sensitivity of the results to including IPOs with zero issue-price update and emphasizes the importance of employing zero-inflated beta regression in scenarios where observations equal zero.

Figure B1 in Appendix B shows the trace plots of the coefficients in Model 10 of Table B1 for zero-inflated beta model.

[Insert Figure B1]

The trace plots of the coefficients for zero-inflated beta model suggest that the Markov chains have mixed well and achieved satisfactory convergence. Markov Chain Monte Carlo (MCMC) is a class of methods used for sampling from complex probability distributions (Liu et al., 2014; Liu et al., 2015). Each sample in an MCMC algorithm is drawn depending on the current state of a Markov Chain, hence the name. The main purpose of MCMC methods is to generate a series of samples, where the sequence of samples approximates the underlying target distribution. The benefit of these methods is that they can be used to sample from distributions that are difficult to handle directly, due to their high dimensionality or complexity. An important aspect of MCMC methods is the idea of "convergence to equilibrium." This means that, as the MCMC algorithm runs, the distribution of the samples it generates becomes closer and closer to the target distribution. This property is key to the ability of MCMC methods to approximate complex distributions. One common tool for checking the convergence of MCMC algorithms is the trace plot. A trace plot shows the values of the samples generated by the MCMC algorithm over time. By examining a trace plot, one can check whether the Markov Chain appears to be converging to a stable distribution (indicating that the algorithm is doing a good job of approximating the target distribution) or whether it is still "exploring" the space of possible values (indicating that the algorithm may need more time to converge).

6.2 Extended data set

We acknowledge that the number of lottery IPOs with no pre-commitment from institutional investors (14 IPOs) in our data sample may not be adequate for drawing causal inferences in regressions where the dependent variable is issue-price update or price volatility. This limited sample size poses a challenge for statistical analysis, as it can lead to less reliable estimates and weaker statistical power, potentially skewing the results and limiting the generalizability of the findings.

To address this concern and enhance the robustness of our analysis, we extend the period under study to include IPOs from November 2005 to March 2019. By expanding the dataset, we aim to increase the sample size, particularly the number of lottery IPOs with no pre-commitment from institutional investors, thereby improving the reliability and validity of our regression results. This expanded dataset also helps ensure that our findings are not driven by a specific subset of IPOs but rather reflect broader market dynamics over a longer timeframe. The summary statistics for the extended period are presented in Tables B2 and B3.

[Insert Table B2]

[Insert Table B3]

The summary statistics of the extended data shown Table B2 shows that the mean, median, and standard deviation (SD) values of the issue-price update in lottery IPOs are relatively lower with institutional pre-commitment (43 IPOs) compared to without (96 IPOs). This observation is consistent with that in Table 3 and further aligns with the prediction of Hypothesis H1. The table also shows that the mean, median, and standard deviation of both price volatility and issue-price update in pro-rata IPOs are relatively lower with institutional pre-commitment (95 IPOs) compared to without (183 IPOs). This observation, which also aligns with the observations in Table 3, supports the predictions of H1 and H2. Moreover, the mean, median, and standard deviation values of price volatility in lottery IPOs in Table B2, as in Table 3 are similar with and without institutional pre-commitment, which also aligns with the predictions of H2.

Table B3 indicates that IPO characteristics in the data sample are not homogenous across years. Specifically, the table shows that the mean, median, and SD of IPO characteristics are not homogenous across years. This suggests the importance of controlling for year fixed-effects, in addition to controlling for industry fixed-effects, in the regressions. These findings of the extended period November 2005 to March 2019 are in line with the period July 2009 to March 2019.

Next, we replicate results of Table 5 and 6 using extended period from November 2005 to March 2019. The results are reported in Table B4 and A5, respectively.

[Insert Table B4]

[Insert Table B5]

Not surprisingly, the overall results of beta regressions using the extended data, as shown in Tables B4 and B5, are consistent with those reported in Tables 5 and 6, respectively. Similarly, the residual plots shown in Figures B2 and B3 match with those of Figure 6 and Figure 7, suggesting that the model is a good fit for data.

[Insert Figure B2]

[Insert Figure B3]

This consistency confirms the predictions of our hypotheses and reinforces the robustness of our findings. The extended analysis supports the initial results, demonstrating that the relationships and effects observed in the original sample hold true over a longer period and across a broader dataset.

7. Summary and conclusion

This study demonstrates that institutional commitment prior to public filing reduces uncertainty and information asymmetry, and thereby promotes price discovery in IPO markets where shares are allocated proportionally to all bidders without bias toward investor type, whether retail or institutional. Conversely, institutional commitment prior to public filing has little to no effect on price discovery in scenarios where shares are assigned randomly. This is because price volatility in such IPO shares is primarily influenced by investors bidding and trading strategically as opposed in uncertainty and information in the IPO market.

The multi-dimensional relationship between the allocation of IPO shares and post-IPO market dynamics underscores the importance of considering not just the economic uncertainties associated with the value of the IPO, but also the psychological and strategic behaviors of investors when analyzing their impact on market outcomes in auction IPO settings. The method of share allocation, whether by random lottery or proportional distribution, not only affects investor psychology and behavior but also shapes the overall market stability and efficiency following the IPO. This dual consideration of economic principles and investor psychology is crucial for a comprehensive analysis of how various elements contribute to market dynamics in general, and auction IPOs in particular.

The study recognizes the risk measurement error poses to causal inferences in empirical research, and that correct model specification, tailored to the data type at hand, is crucial for more accurate parameter estimation and meaningful interpretation. Both price volatility and issue-price update in our data sample are beta distributed, meaning they are continuous and bounded between 0 and 1. Thus, we use beta regression approach, which is the appropriate approach when using data that is beta-distributed, in our analysis.

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TABLES AND FIGURES

Table 1: This table shows the descriptive statistics of variables used in the analysis. The dataset consists of 226 IPOs in India between July 2009 and March 2019. Panel A shows the primary summary statistics for all variables. Panel B shows the summary statistics for all variables with logarithm transformation of issue amount, institutional demand, and retail demand. The variables are defined in Appendix A.

Panel A: Summary statistics					
	Median	Mean	SD	Min	Max
Price Volatility	0.02	0.03	0.01	0.01	0.08
Issue-price Update	0.03	0.03	0.02	0.00	0.09
Underpricing	0.04	0.12	0.31	-0.64	1.53
Issue Amount	3961975000	8,862,404,137.00	17,929,878,850.00	230,045,000.00	151,994,402,000.00
Institutional Demand	2.76	12.57	20.29	0.03	143.62
Retail Demand	2.53	5.56	8.59	0.02	74.37
EPS	6.96	10.24	17.53	-97.75	170.30
Retained Equity	0.78	0.78	0.12	0.42	1.00
Panel B: Summary statistics with logarithm transformation					
	Median	Mean	SD	Min	Max
Price Volatility	0.02	0.03	0.01	0.01	0.08
Issue-price Update	0.02	0.03	0.02	0.001	0.09
Underpricing	0.04	0.12	0.31	-0.64	1.53
Ln(Issue Amount)	22.11	21.97	1.34	19.75	25.75
Ln(Institutional Demand)	1.01	1.36	1.64	-3.46	4.97
Ln(Retail Demand)	0.93	0.89	1.39	-3.91	4.31
EPS	6.89	10.10	17.47	-97.75	170.30
Retained Equity	0.78	0.78	0.42	0.419	1.00

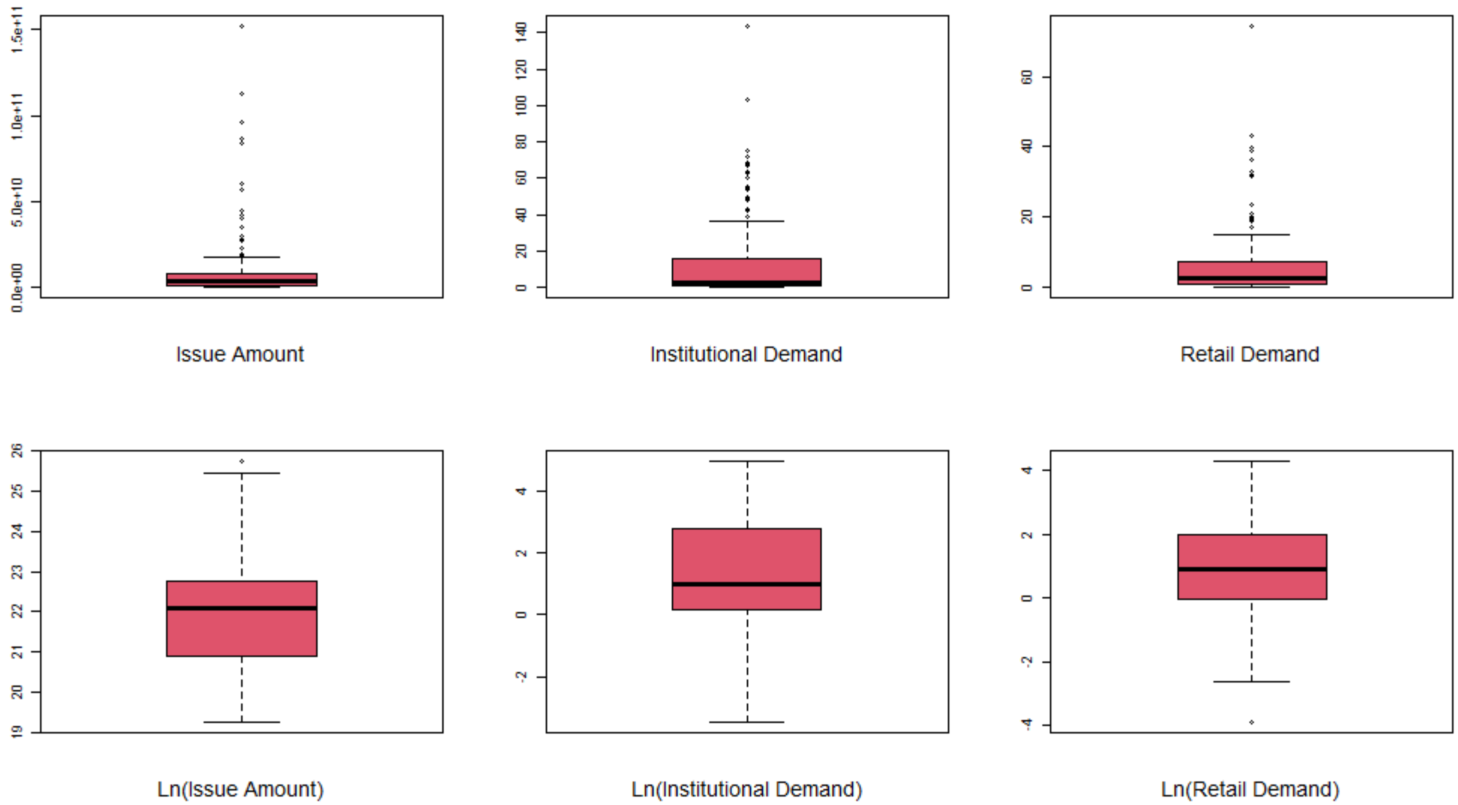

Figure 1. The boxplots for independent variables, issue amount, institutional demand, and retail demand before and after logarithm transformation.

Table 2: This table presents Pearson partial correlation of the variables used in the analysis. The dataset consists of 226 IPO in India between July 2009 and March 2019. The corresponding significance levels (if no asterisks, the independent is not statistically significant, while asterisks ***, **, and * denote significance at the 1%, 5%, and 10%, respectively). The variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price Volatility	1.00							
Issue-price Update	0.28***	1.00						
Underpricing	0.28***	-0.04	1.00					
Ln(Issue Amount)	-0.63***	-0.28***	-0.10	1.00				
Ln(Institutional Demand)	-0.43***	-0.27***	0.36***	0.42***	1.00			
Ln(Retail Demand)	0.16*	0.02	0.39***	-0.27***	0.42***	1.00		
EPS	-0.20**	-0.12	0.09	0.17*	0.28***	0.15*	1.00	
Retained Equity	-0.53***	-0.27***	0.03	0.57***	0.55***	0.05	0.15*	1.00

*p<0.1; **p<0.05; ***p<0.01.

Table 3: This table shows summary statistics by lottery pre-commitment and pro-rata pre-commitment. This table shows the number of IPOs, mean, median, and standard deviation (SD) of the variables used in the analysis by lottery pre-commitment and pro-rata pre-commitment. The dataset consists of 226 IPOs in India between July 2009 and March 2019. The variables shown in the table are defined in Appendix A.

Number of IPOs and mean, median, and standard deviation of IPO characteristics by lottery pre-commitment and pro-rata pre-commitment.												
	Lottery No Pre-commitment			Lottery Yes Pre-commitment			Pro-rata No Pre-commitment			Pro-rata Yes Pre-commitment		
Number of IPOs	(14)			(43)			(74)			(95)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Price Volatility	0.021	0.015	0.011	0.019	0.019	0.007	0.036	0.032	0.018	0.020	0.018	0.009
Issue-price Update	0.039	0.039	0.020	0.023	0.016	0.020	0.041	0.039	0.022	0.023	0.018	0.020
Underpricing	0.295	0.208	0.356	0.332	0.305	0.253	0.089	-0.003	0.402	0.020	0.0003	0.149
Ln(Issue Amount)	22.416	22.262	1.746	22.466	22.309	0.897	20.969	20.527	1.266	22.435	22.353	1.047
Ln(Institutional Demand)	3.922	3.945	0.514	3.432	3.438	0.474	-0.125	0.021	1.188	1.166	0.957	0.758
Ln(Retail Demand)	2.440	2.432	1.074	1.942	2.048	0.896	0.809	0.859	1.165	0.239	0.262	1.310
EPS	17.936	10.795	23.864	16.464	9.690	26.128	7.942	6.330	10.903	8.075	6.920	14.960
Retained Equity	0.827	0.844	0.067	0.857	0.876	0.072	0.680	0.668	0.123	0.806	0.802	0.091

Table 4: This table shows the descriptive statistics of the variables used in the analysis of IPO characteristics by year. The dataset consists of 226 IPOs in India between July 2009 and March 2019. The variables are defined in Appendix A.

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Number of IPOs	15	62	30	9	3	5	20	24	32	24	2
					Mean						
Price Volatility	0.026	0.026	0.042	0.023	0.020	0.028	0.022	0.019	0.018	0.019	0.026
Issue-price Update	0.041	0.039	0.043	0.039	0.031	0.034	0.029	0.026	0.012	0.009	0.020
Underpricing	0.111	0.127	0.101	0.030	0.022	0.261	0.088	0.131	0.188	0.075	-0.036
Ln(Issue Amount)	21.518	21.554	20.804	21.710	21.775	21.517	22.276	22.536	22.925	22.856	21.388
Ln(Institutional Demand)	0.890	1.501	-0.390	1.297	1.095	2.213	1.410	1.713	2.190	1.770	0.721
Ln(Retail Demand)	0.348	0.987	1.086	0.378	0.050	2.283	0.280	1.031	1.491	0.470	-1.537
EPS	12.333	11.739	5.991	11.921	8.247	11.508	9.126	12.536	8.584	15.393	-47.840
Retained Equity	0.753	0.746	0.676	0.783	0.828	0.780	0.821	0.831	0.827	0.826	0.729
					Median						
Price Volatility	0.020	0.022	0.039	0.022	0.022	0.028	0.021	0.019	0.015	0.018	0.026
Issue-price Update	0.034	0.035	0.045	0.038	0.024	0.037	0.022	0.016	0.009	0.007	0.020
Underpricing	0.023	0.087	0.007	0.001	-0.023	0.261	0.026	0.136	0.032	0.000	-0.036
Ln(Issue Amount)	20.854	21.366	20.591	21.308	21.717	21.403	22.313	22.445	22.652	22.969	21.388
Ln(Institutional Demand)	0.075	1.290	-0.248	1.349	0.955	2.487	0.904	1.628	1.824	1.629	0.721
Ln(Retail Demand)	0.548	1.155	1.048	0.470	-0.315	1.991	0.329	0.739	1.753	0.274	-1.537
EPS	9.140	7.130	3.620	8.490	5.910	10.310	6.845	10.690	7.465	9.520	-47.840
Retained Equity	0.754	0.779	0.727	0.806	0.846	0.748	0.843	0.846	0.849	0.862	0.729
					SD						
Price Volatility	0.017	0.014	0.018	0.010	0.003	0.008	0.008	0.008	0.010	0.009	0.016
Issue-price Update	0.026	0.018	0.023	0.030	0.014	0.013	0.019	0.024	0.011	0.007	0.016
Underpricing	0.364	0.279	0.507	0.122	0.116	0.329	0.188	0.203	0.344	0.231	0.103
Ln(Issue Amount)	1.672	1.240	0.972	1.300	1.139	0.462	0.815	0.916	1.217	0.990	3.018
Ln(Institutional Demand)	1.771	1.819	1.312	1.066	0.780	0.764	1.249	1.157	1.522	1.356	0.284
Ln(Retail Demand)	1.017	1.589	1.089	1.378	1.037	0.797	0.944	1.024	1.283	1.464	3.358

EPS	22.631	22.154	8.890	11.686	4.125	8.597	14.964	12.087	9.471	13.995	70.583
Retained Equity	0.122	0.128	0.113	0.144	0.074	0.066	0.081	0.091	0.093	0.104	0.022

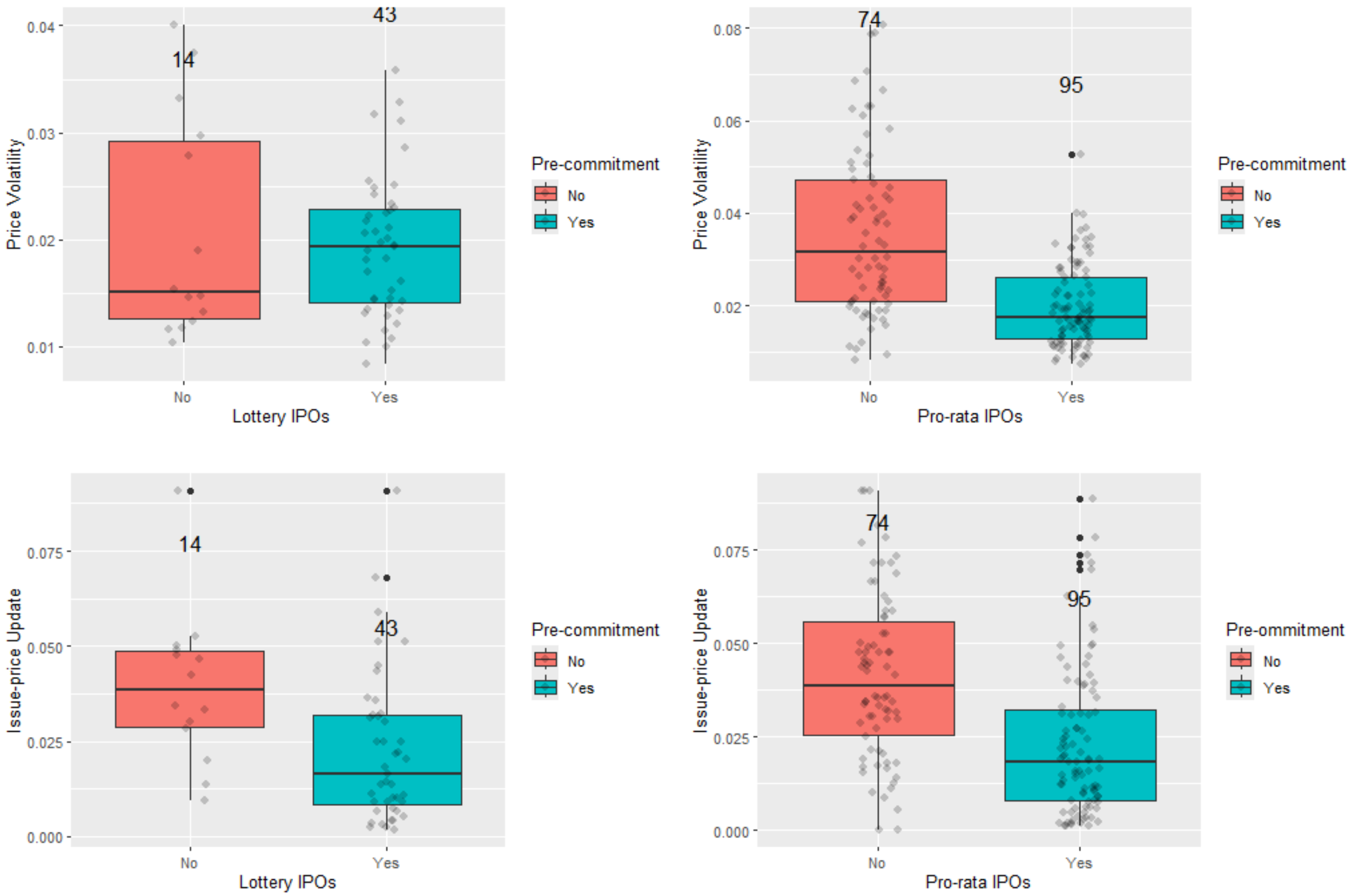

Figure 2. Boxplots for Table 3 reflecting the median and number of IPOs of the price volatility and issue-price update with respect to the lottery pre-commitment and pro-rata pre-commitment considered in the analysis between July 2009 and March 2019 in India.

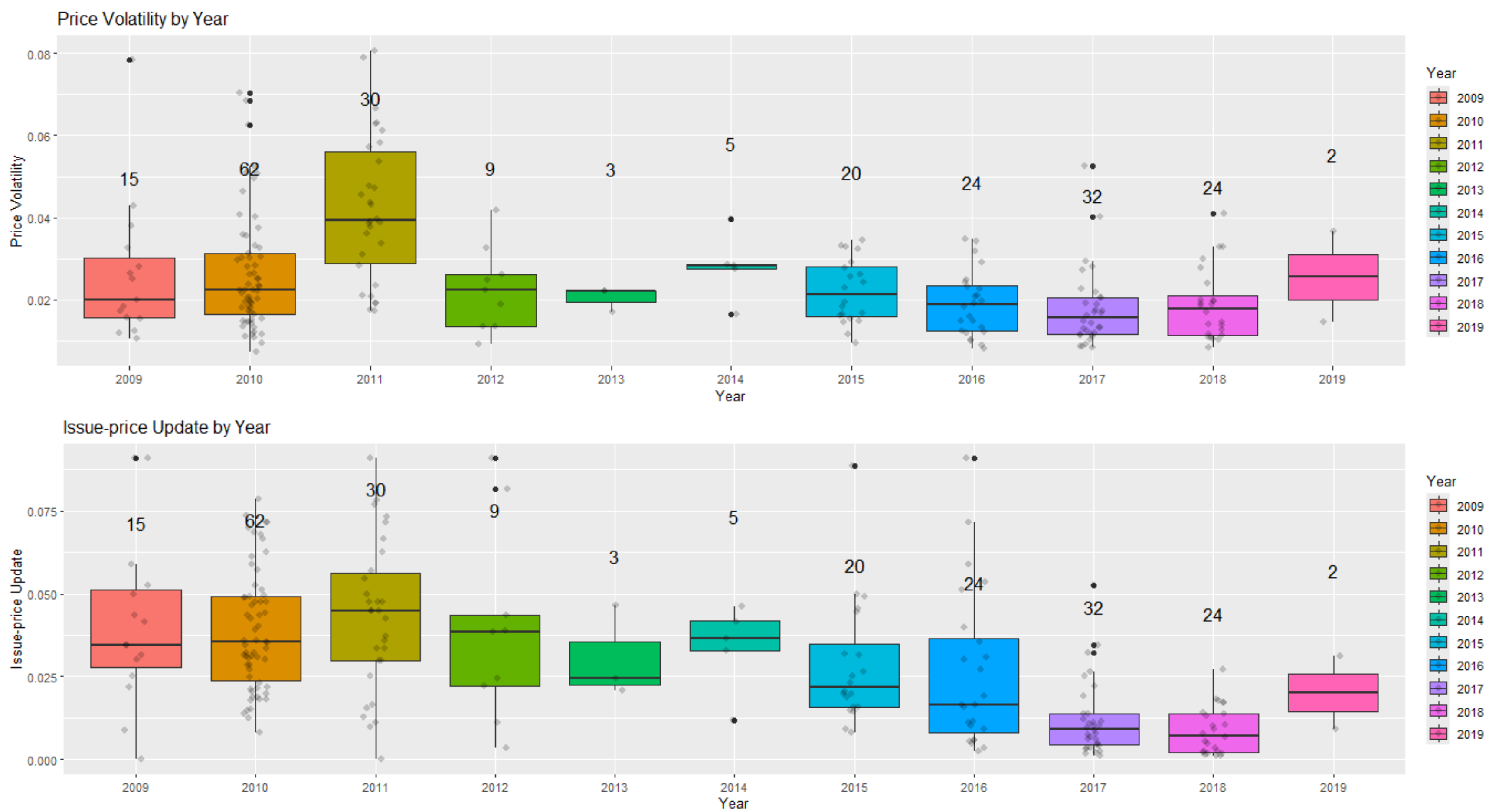

Figure 3. Boxplot for Table 4 reflecting the median and number of IPOs of the price volatility and issue-price update by year prior to public filing considered in the analysis between July 2009 and March 2019 in India.

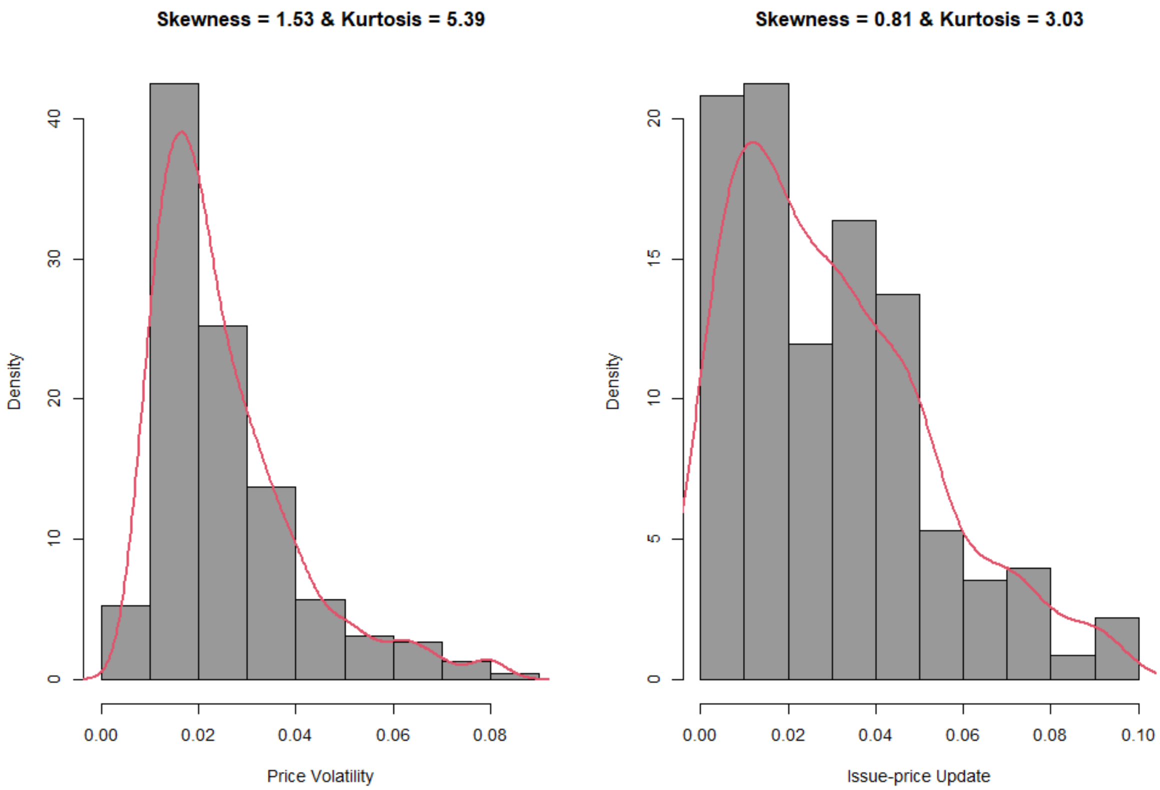

Figure 4. The histogram with the density curve, skewness, and kurtosis for price volatility and issue-price update.

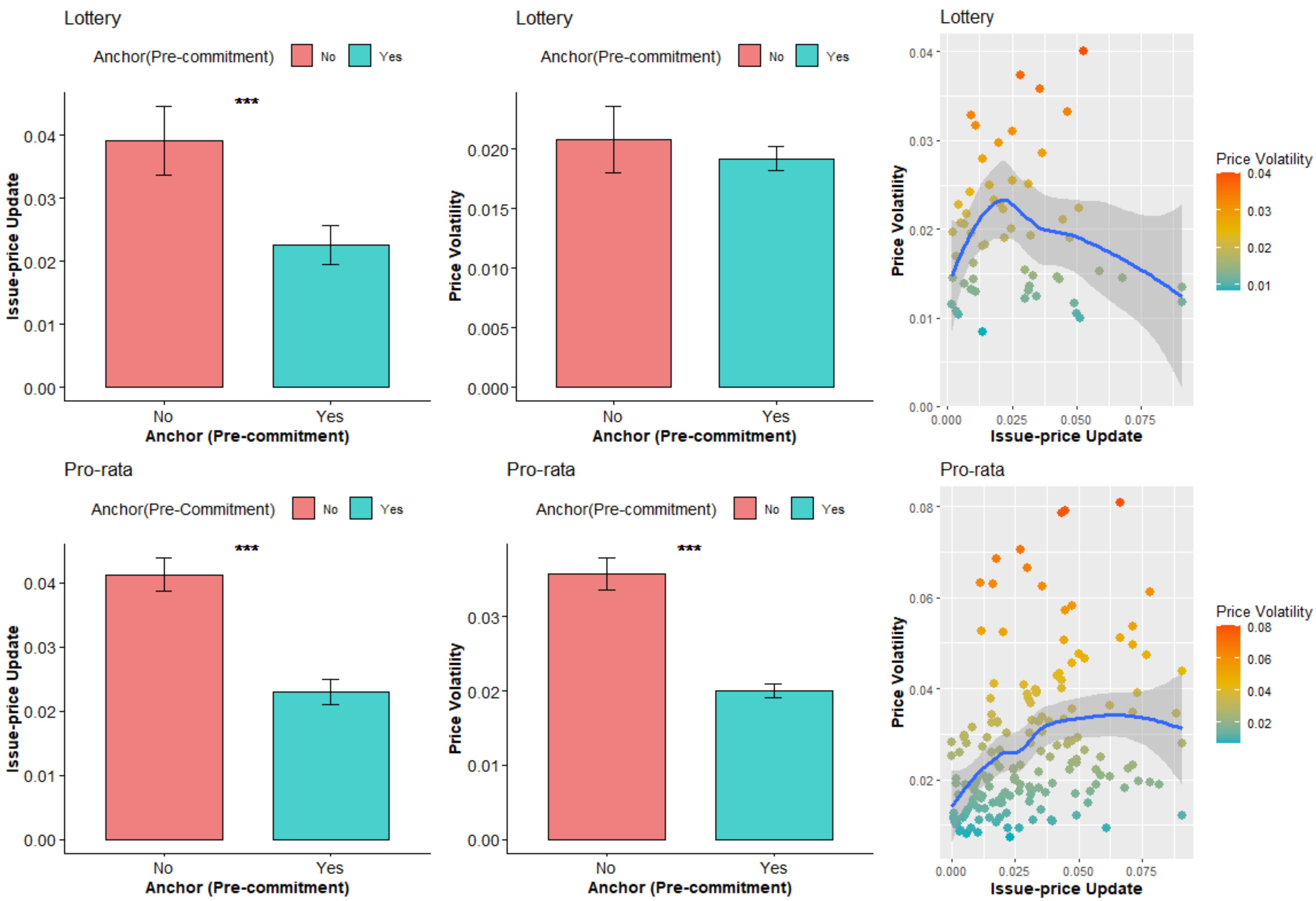

Figure 5. The bar charts with standard errors compare issue-price update and price volatility in IPOs with institutional pre-commit and IPOs without pre-commitment, both when shares are randomly assigned and when the assignment is based on a lottery system. The scatter plots show the relationship between price volatility and issue-price update lottery-based and pro-rata-based IPOs. ***, **, and * indicate significance at the 1%, 5%, and 10%, respectively.

Table 5: This table presents the results of beta regressions with Issue-price update as the dependent variable and lottery pre-commitment and pro-rata pre-commitment as the key independent variables. The reference category in Models (1) through (8) is pro-rata IPOs with no pre-commitment from institutional investors. The dataset consists of 224 IPOs in India between July 2009 and March 2019 (two IPOs with issue-price update equal to zero are excluded). Robust standard errors are reported in brackets. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix A.

	Issue-price Update (Beta Regressions)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-3.086***	-3.025***	-4.427***	-5.022***	-3.244**	-3.600***	-3.606***	-3.957***
	(0.069)	(0.120)	(0.901)	(0.882)	(1.360)	(1.378)	(1.348)	(1.364)
Lottery Pre-commitment	-0.645***	-0.467***	-0.352**	-0.476***	-0.363**	-0.367**		
	(0.190)	(0.168)	(0.179)	(0.171)	(0.179)	(0.184)		
Pro-rata Pre-commitment	-0.717***	-0.508***	-0.389***	-0.569***	-0.453***	-0.472***		
	(0.101)	(0.101)	(0.114)	(0.114)	(0.122)	(0.123)		
Lottery IPO	-0.058	0.048	0.046	0.031	0.010	-0.006	0.318*	0.266
	(0.168)	(0.148)	(0.169)	(0.164)	(0.172)	(0.174)	(0.172)	(0.174)
Ln(Issue Amount)			0.028	0.094**	-0.015	0.003	-0.005	0.012
			(0.043)	(0.043)	(0.060)	(0.061)	(0.059)	(0.060)
EPS			-0.006**	-0.004*	-0.005*	-0.004	-0.003	-0.003
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Retained Equity			0.140	-0.007	0.092	0.053	0.411	0.377
			(0.452)	(0.435)	(0.448)	(0.466)	(0.453)	(0.474)
Offer-for-sale			-0.001	0.020	-0.009	-0.022	-0.056	-0.061
			(0.136)	(0.126)	(0.137)	(0.137)	(0.137)	(0.137)
Appraised IPO			0.168	0.236*	0.133	0.136	0.146	0.156
			(0.146)	(0.140)	(0.147)	(0.149)	(0.144)	(0.145)
Graded IPO			0.748***	0.135	0.687***	0.657***	0.680***	0.653***
			(0.112)	(0.179)	(0.184)	(0.184)	(0.182)	(0.183)
Promoter Sell			0.058	0.202	0.047	0.021	0.059	0.029
			(0.158)	(0.152)	(0.159)	(0.163)	(0.158)	(0.163)
VC Sell			-0.041	-0.005	-0.041	-0.037	-0.036	-0.040

			(0.146)	(0.135)	(0.147)	(0.147)	(0.146)	(0.147)
Underwriter Reputation			-0.166	-0.333**	-0.141	-0.152	-0.144	-0.157
			(0.143)	(0.135)	(0.144)	(0.146)	(0.143)	(0.144)
Auditor Reputation			0.015	0.296	0.047	-0.008	0.092	0.025
			(0.274)	(0.263)	(0.280)	(0.282)	(0.282)	(0.285)
Amount < 2.5b					-0.238	-0.236	-0.305*	-0.306*
					(0.173)	(0.174)	(0.173)	(0.174)
Post 2012					-0.127	-0.165	-0.127	-0.168
					(0.204)	(0.206)	(0.203)	(0.206)
Amount < 2.5b × Post 2012					0.279	0.365*	0.386*	0.472**
					(0.206)	(0.212)	(0.208)	(0.214)
Ln(Institutional Demand)							-0.122***	-0.116***
							(0.044)	(0.045)
Pre-commitment							-0.485***	-0.534***
							(0.150)	(0.151)
Ln(Institutional Demand) × Pre-commitment							0.046	0.066
							(0.063)	(0.064)
Year FE	No	Yes	No	Yes	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of Obs.	224	224	224	224	224	224	224	224
Pseudo R^2	0.187	0.528	0.379	0.567	0.390	0.402	0.398	0.411
φ	62.54	99.20	83.14	106.35	84.07	86.09	87.04	88.87
RMSE	0.020	0.017	0.018	0.017	0.018	0.018	0.018	0.018

*p<0.1; **p<0.05; ***p<0.01

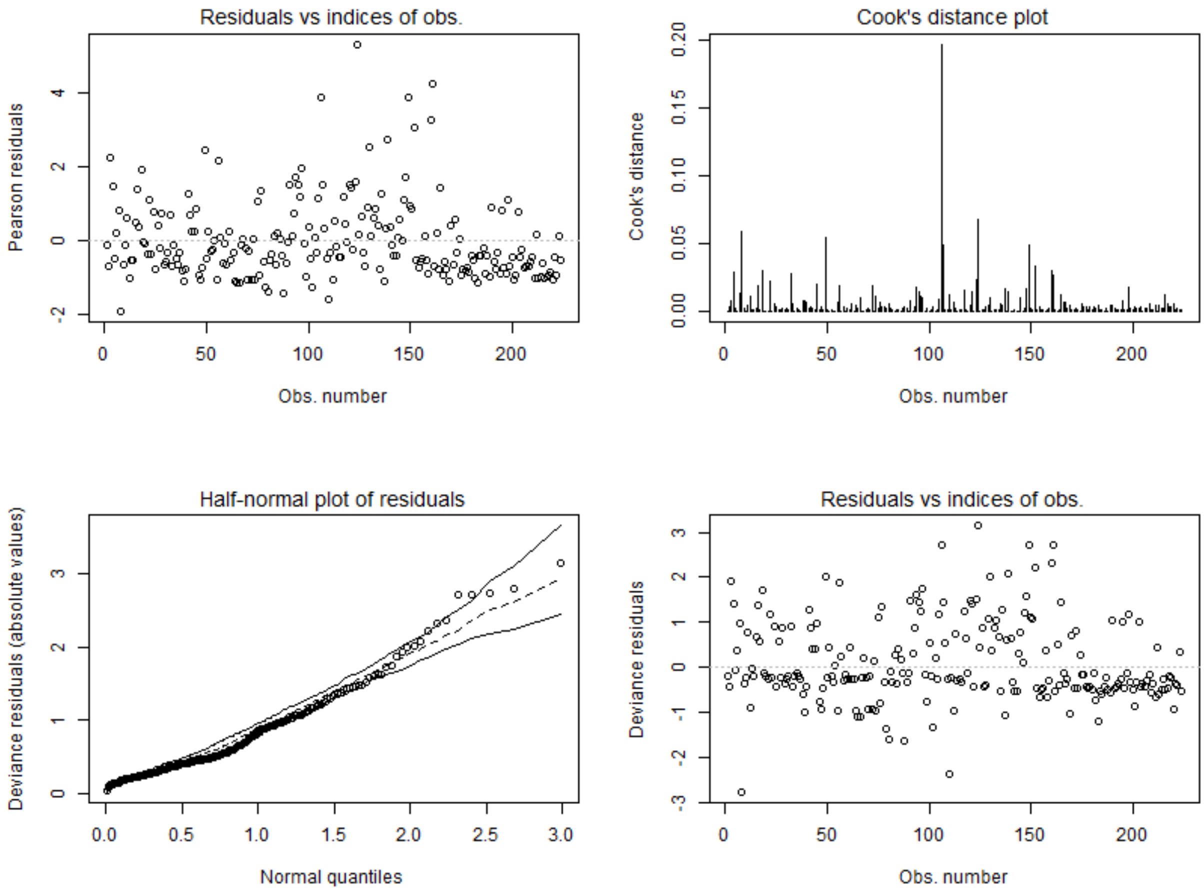

Figure 6. Diagnostic plots for the beta regression Model 6 in Table 5. The upper left panel is the plot of Pearson residuals versus the number of observations, the upper right panel is the Cook's distance versus the number of observations, the lower left panel displays the half-normal plot of absolute deviance residuals with simulated envelope, the lower right panel is the plot of deviance residuals versus the number of observations.

Table 6: This table reports the results of beta regressions with price volatility as the dependent variable and issue-price update, lottery pre-commitment, pro-rata pre-commitment, pro-rata IPOs, and their interaction terms, as the key independent variables. The reference category in Models (1) through (6) is pro-rata IPOs with no pre-commitment from institutional investors. The dataset consists of 226 IPOs in India between July 2009 and March 2019. All variables are defined in Appendix A. Robust standard errors are reported in brackets. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively.

	Price Volatility (Beta Regressions)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	-3.408***	0.060	-0.286	-0.235	-1.384	-1.531*	-1.543*	-1.676*	-1.546*	-1.670*	-1.463	-1.589*	-1.489	-1.613*
	(0.092)	(0.618)	(0.674)	(0.699)	(0.920)	(0.924)	(0.931)	(0.933)	(0.929)	(0.932)	(0.923)	(0.928)	(0.922)	(0.926)
Issue-price update	1.330	-1.522	-2.017	-1.950	-1.949	-2.059	0.644	0.567	0.651	0.544	-1.896	-1.962	-1.824	-1.910
	(1.919)	(1.578)	(1.646)	(1.598)	(1.638)	(1.610)	(1.226)	(1.204)	(1.214)	(1.194)	(1.652)	(1.621)	(1.640)	(1.611)
Lottery Pre-commitment	0.051	-0.100	-0.108	-0.091	-0.110	-0.116								
	(0.185)	(0.150)	(0.154)	(0.149)	(0.154)	(0.154)								
Pro-rata Pre-commitment	-0.609***	-0.306***	-0.279***	-0.261**	-0.266**	-0.246**								
	(0.120)	(0.105)	(0.108)	(0.106)	(0.110)	(0.108)								
Issue-price update × Lottery Pre-commitment	-2.194	-0.199	0.915	0.903	1.400	1.912								
	(4.218)	(3.487)	(3.590)	(3.441)	(3.591)	(3.507)								
Issue-price update × Pro-rata Pre-commitment	5.646*	6.593***	6.827***	5.393**	7.034***	6.953***								
	(3.020)	(2.432)	(2.512)	(2.429)	(2.495)	(2.436)								
Lottery IPO	-0.484***	-0.037	0.003	-0.050	0.002	-0.004	0.004	-0.011			0.042	0.034		
	(0.134)	(0.151)	(0.151)	(0.149)	(0.152)	(0.152)	(0.097)	(0.096)			(0.107)	(0.106)		
Underpricing		0.401***	0.414***	0.376***	0.404***	0.391***	0.400***	0.384***	0.400***	0.383***	0.420***	0.403***	0.420***	0.404***
		(0.067)	(0.069)	(0.066)	(0.069)	(0.068)	(0.070)	(0.068)	(0.069)	(0.068)	(0.070)	(0.069)	(0.070)	(0.069)
Ln(Issue Amount)		-0.163***	-0.138***	-0.128***	-0.095**	-0.084**	-0.089**	-0.079*	-0.089**	-0.079*	-0.091**	-0.081**	-0.090**	-0.080*
		(0.029)	(0.032)	(0.034)	(0.041)	(0.041)	(0.041)	(0.042)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Ln(Institutional Demand)		-0.072**	-0.092***	-0.057*	-0.087***	-0.081***	-0.079***	-0.071***	-0.079***	-0.073***	-0.062	-0.064	-0.056	-0.059
		(0.030)	(0.029)	(0.030)	(0.029)	(0.029)	(0.028)	(0.027)	(0.022)	(0.021)	(0.048)	(0.048)	(0.045)	(0.045)
Pre-commitment											-0.224*	-0.196	-0.235*	-0.205
											(0.135)	(0.133)	(0.133)	(0.131)
Ln(Retail Demand)		0.016	0.037	0.026	0.038	0.035	0.038	0.033	0.038*	0.033	0.038	0.035	0.039*	0.037
		(0.025)	(0.024)	(0.025)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)
EPS			-0.003*	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003*	-0.003**	-0.003*
			(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Retained Equity			-0.236	-0.430	-0.208	-0.372	-0.311	-0.463*	-0.311	-0.463*	-0.241	-0.400	-0.241	-0.401
			(0.269)	(0.269)	(0.269)	(0.272)	(0.266)	(0.270)	(0.266)	(0.270)	(0.271)	(0.275)	(0.271)	(0.275)
Offer-for-sale			-0.121	-0.141*	-0.121	-0.127	-0.142*	-0.149*	-0.142*	-0.149*	-0.134	-0.142*	-0.130	-0.138*
			(0.084)	(0.082)	(0.084)	(0.083)	(0.084)	(0.082)	(0.084)	(0.082)	(0.085)	(0.084)	(0.085)	(0.083)
Appraised IPO			0.063	0.101	0.078	0.085	0.059	0.061	0.059	0.061	0.071	0.082	0.072	0.083

			(0.090)	(0.089)	(0.090)	(0.090)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.090)	(0.091)	(0.090)
Graded IPO			0.002	-0.099	0.016	0.011	0.026	0.025	0.026	0.026	0.022	0.017	0.017	0.014
			(0.069)	(0.115)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.109)	(0.112)	(0.111)	(0.111)	(0.111)
Promoter Sell			0.038	0.087	0.047	0.065	0.073	0.093	0.072	0.094	0.056	0.077	0.051	0.073
			(0.090)	(0.090)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.092)	(0.092)	(0.091)	(0.091)
VC Sell			0.025	0.045	0.037	0.051	0.037	0.055	0.037	0.055	0.050	0.068	0.047	0.065
			(0.087)	(0.084)	(0.086)	(0.085)	(0.086)	(0.084)	(0.086)	(0.084)	(0.087)	(0.086)	(0.087)	(0.086)
Underwriter Reputation			0.059	0.021	0.039	0.004	0.016	-0.013	0.016	-0.012	0.034	-0.001	0.031	-0.003
			(0.089)	(0.087)	(0.089)	(0.089)	(0.090)	(0.089)	(0.089)	(0.089)	(0.090)	(0.090)	(0.090)	(0.089)
Auditor Reputation			-0.093	-0.104	-0.112	-0.134	-0.127	-0.142	-0.128	-0.140	-0.093	-0.109	-0.100	-0.116
			(0.168)	(0.167)	(0.170)	(0.170)	(0.172)	(0.171)	(0.170)	(0.170)	(0.171)	(0.171)	(0.169)	(0.168)
Amount < 2.5b					0.195*	0.247**	0.198*	0.240**	0.199*	0.239**	0.204*	0.256**	0.207*	0.258**
					(0.111)	(0.110)	(0.109)	(0.108)	(0.109)	(0.107)	(0.112)	(0.111)	(0.112)	(0.111)
Post 2012					0.074	0.088	0.049	0.062	0.049	0.063	0.081	0.100	0.075	0.095
					(0.126)	(0.126)	(0.127)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.125)	(0.125)
Amount < 2.5b × Post 2012					-0.107	-0.154	-0.104	-0.139	-0.104	-0.137	-0.114	-0.169	-0.114	-0.169
					(0.121)	(0.124)	(0.119)	(0.120)	(0.119)	(0.120)	(0.123)	(0.126)	(0.123)	(0.126)
Issue-price update × Ln(Institutional Demand)											-0.521	-0.321	-0.550	-0.352
											(0.865)	(0.874)	(0.864)	(0.871)
Issue-price update × Pre-commitment											7.271**	7.014**	7.274**	7.025**
											(3.065)	(2.993)	(3.068)	(2.995)
Ln(Institutional Demand) × Pre-commitment											-0.016	-0.017	-0.010	-0.013
											(0.061)	(0.060)	(0.059)	(0.058)
Issue-price update × Ln(Institutional Demand) × Pre-commitment											-0.697	-0.696	-0.675	-0.675
											(1.527)	(1.495)	(1.530)	(1.497)
Year FE	No	Yes	No	Yes	No	No	No	No	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of Obs.	226	226	226	226	226	226	226	226	226	226	226	226	226	226
Pseudo R^2	0.273	0.586	0.581	0.620	0.588	0.603	0.569	0.585	0.569	0.586	0.585	0.600	0.583	0.599
φ	191.20	361.01	342.01	389.45	346.86	365.79	334.27	352.55	334.27	352.52	345.81	364.75	345.61	364.60
RMSE	0.012	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009

*p<0.1; **p<0.05; ***p<0.01

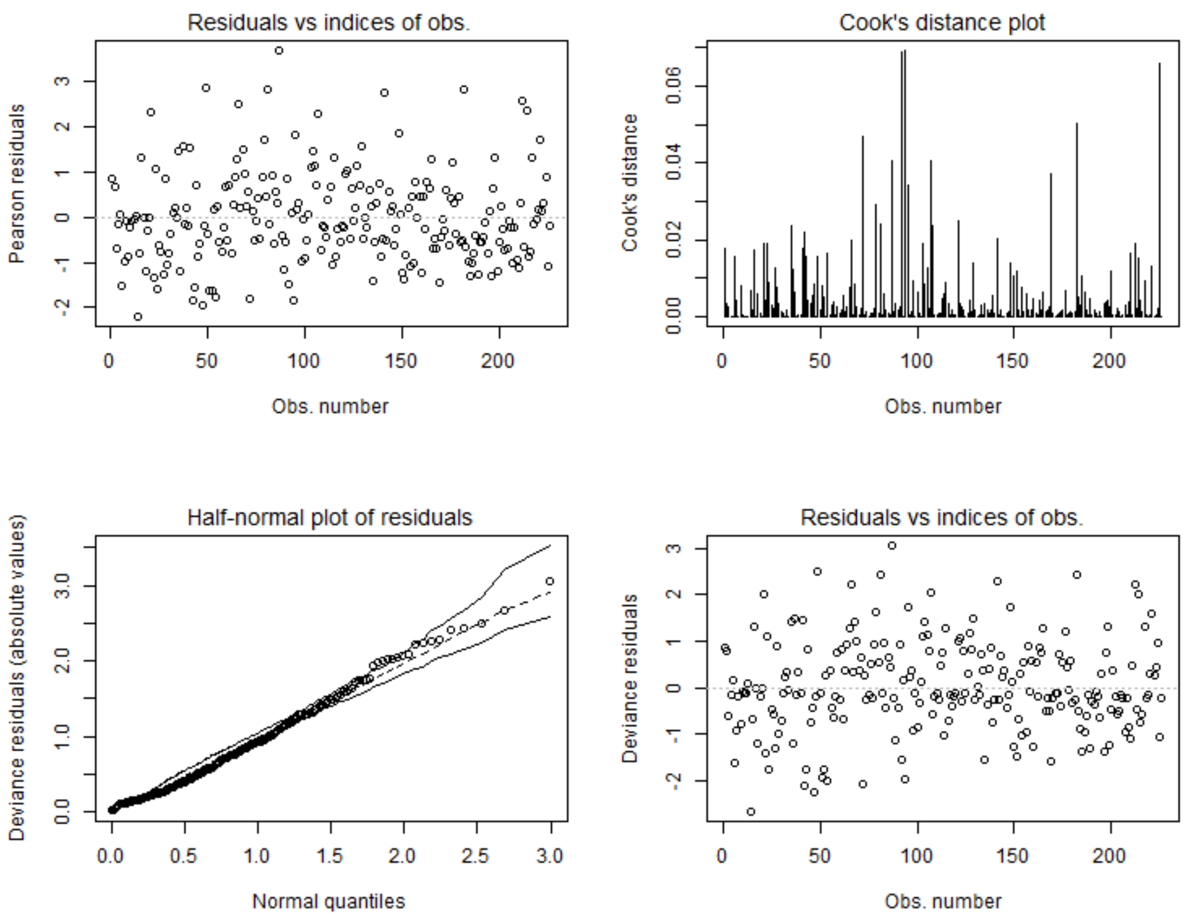

Figure 7. Diagnostic plots for the beta regression Model 6 in Table 6. The upper left panel is the plot of Pearson residuals versus the number of observations. The upper right panel is the Cook's distance versus the number of observations. The lower left panel displays the half-normal plot of absolute deviance residuals with simulated envelope, and the lower right panel is the plot of deviance residuals versus the number of observations.

APPENDIX A

List of variable definitions

Price Volatility	Average daily price volatility during the initial 30 days of trading: $\frac{\sum_{t=1}^{30}\left(\sqrt{\left(\left(\frac{Closing\ Price_{t+1}}{Closing\ Price_t}\right)-1\right)^2}\right)}{30}$ where *t=1* is the first day of trading.
Lottery IPO	Takes a value of 1 if shares are randomly assigned to investors, and zero otherwise. This situation arises when the IPO is heavily oversubscribed and proportional allocation of shares violates the minimum lot size requirement policy.
Pro-rata IPO	Takes a value of 1 if IPO shares proportionally assigned to investors, and zero otherwise.
Lottery Pre-commitment	Takes a value of 1 if anchor institutional investors pre-commit to purchasing IPO shares and shares to non-anchor investors are randomly assigned, and zero otherwise.
Pro-rata Pre-commitment	Takes a value of 1 if anchor institutional investors pre-commit to purchasing IPO shares and shares to non-anchor investors are proportionally assigned, and zero otherwise.
Filing-price Range	The price range set by the underwriter prior to the bidding phase.
Issue-price	The price at which IPO shares are offered to investors in the primary market.
Issue-price update	|(Issue-price / midpoint of Filing-price Range) –1|.
Institutional Demand	Times IPO is oversubscribed by non-anchor institutional investors.
Retail Demand	Times IPO is oversubscribed by retail investors.
Issue Amount	Issue-price × number of shares issued.
Retained Equity	The ratio of majority shareholders' post-issue shares (%) to their pre-issue shares (%).
Underpricing	(The closing price on the first trading day / Issue-price) –1.
Appraised	Takes a value of 1 if IPO is appraised by a SEBI approved appraiser, and zero otherwise
Graded	Takes a value of 1 if IPO is graded by a SEBI approved grading agency, and zero otherwise
Offer-for-sale	Takes a value of 1 if IPO also includes transfer of shares, and zero otherwise.
Underwriter Reputation	Takes a value of 1 if the underwriter of the IPO is in the top quartile —underwriter with the most deals and the highest proceeds, and 0 otherwise.
Auditor Reputation	Takes a value of 1 if the auditor(s) of the IPO is one of the "Big 4" accounting and auditing firms in India —Deloitte, Ernst and Young, PWC, and KPMG, and 0 otherwise.
Promoter Sell	Takes a value of 1 if promoters are selling their shares, and zero otherwise.
VC Sell	Takes a value of 1 if the venture capitalists are selling their shares, and zero otherwise.
Post 2012	Takes a value of 1 if the IPO is listed on or after January 1, 2012, and zero if prior to 2012.
Amount < 2.5b	Takes a value of 1 if the issue amount is less than INR 2.5 billion, and zero if more than INR 2.5 billion.
EPS	Earnings-per-share reported in the IPO prospectus.

APPENDIX B

Table B1: In this table, we report results of zero-inflated beta regressions with issue-price update as the dependent variable. The dataset consists of 226 IPOs between July 2009 and March 2019 (IPOs with issue-price update equal to zero are included). All variables are defined in Appendix A. Robust standard errors with 95% posterior confidence interval are reported in brackets. ** indicates 95% posterior confidence interval is significant at 5%.

	Issue-price update (Zero-Inflated Beta Regressions)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-3.151**	-3.189**	-4.403**	-4.501**	-3.260**	-3.554**	-3.638**	-3.752**
	(0.008)	(0.009)	(0.065)	(0.043)	(0.077)	(0.096)	(0.077)	(0.077)
	(-3.481, -2.861)	(-3.508, -2.874)	(-6.090, -2.305)	(-6.371, -2.620)	(-6.442, -0.371)	(-6.518, -0.676)	(-6.547, -0.672)	(-6.524, -0.627)
Lottery Pre-Commitment	-0.647**	-0.644**	-0.329	-0.359	-0.344	-0.360		
	(0.010)	(0.010)	(0.008)	(0.010)	(0.010)	(0.008)		
	(-1.026, -0.246)	(-0.998, -0.263)	(-0.667, 0.37)	(-0.712, 0.019)	(-0.741, 0.022)	(-0.733, 0.039)		
Pro-rata Pre-Commitment	-0.705**	-0.730**	-0.383**	-0.393**	-0.439**	-0.473**		
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)		
	(-0.901, -0.513)	(-0.917, -0.517)	(-0.635, -0.159)	(-0.624, -0.157)	(-0.689, -0.179)	(-0.733, -0.236)		
Pro-rata IPO	0.060	0.058	0.034	0.046	-0.007	0.022	0.308	0.270
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)
	(-0.260, 0.428)	(-0.259, 0.400)	(-0.316, 0.33)	(-0.365, 0.354)	(-0.374, 0.304)	(-0.412, 0.304)	(-0.089, 0.638)	(-0.067, 0.591)
Ln(Issue Amount)			0.029	0.035	-0.014	0.002	-0.004	0.003
			(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
			(-0.066, 0.111)	(-0.059, 0.133)	(-0.141, 0.117)	(-0.129, 0.133)	(-0.134, 0.123)	(-0.133, 0.123)
EPS			-0.005	-0.006	-0.005**	-0.004	-0.004**	-0.004
			(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
			(-0.012, 0.0001)	(-0.012, 0.001)	(-0.011, 0.001)	(-0.011, 0.001)	(-0.011, 0.002)	(-0.010, 0.002)
Retained Equity			0.076	0.060	0.075	0.048	0.409	0.382
			(0.022)	(0.025)	(0.024)	(0.025)	(0.024)	(0.024)
			(-0.734, 0.932)	(-0.884, 1.097)	(-0.808, 1.040)	(-0.937, 1.063)	(-0.562, 1.403)	(-0.525, 1.426)
Offer-for-sale			0.010	-0.011	-0.018	-0.022	-0.067	-0.059
			(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)
			(-0.734, 0.932)	(-0.290, 0.283)	(-0.309, 0.20)	(-0.315, 0.265)	(-0.396, 0.211)	(-0.332, 0.240)
Appraised			0.159	0.149	0.133	0.121	0.121	0.154
			(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
			(-0.157, 0.431)	(-0.182, 0.417)	(-0.209, 0.441)	(-0.209, 0.396)	(-0.172, 0.389)	(-0.144, 0.433)
Graded			0.741**	0.724**	0.688**	0.646**	0.670**	0.647**
			(0.006)	(0.006)	(0.010)	(0.010)	(0.011)	(0.010)
			(0.507, 0.990)	(0.471, 0.994)	(0.280, 1.088)	(0.231, 1.044)	(0.300, 1.010)	(0.237, 1.019)
Promoter Sell			0.051	0.034	0.044	0.036	0.066	0.036

			(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
			(-0.270, 0.356)	(-0.327, 0.365)	(-0.262, 0.343)	(-0.259, 0.367)	(-0.241, 0.383)	(-0.291, 0.369)
VC Sell			-0.043	-0.038	-0.036	-0.033	-0.021	-0.043
			(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
			(-0.324, 0.233)	(-0.326, 0.250)	(-0.356, 0.246)	(-0.320, 0.284)	(-0.303, 0.330)	(-0.369, 0.266)
Underwriter Reputation			-0.180	-0.174	-0.145	-0.164	-0.146	-0.161
			(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
			(-0.469, 0.127)	(-0.476, 0.082)	(-0.424 0.175)	(-0.504 0.167)	(-0.426 0.142)	(-0.447 0.125)
Auditor Reputation			-0.047	-0.068	0.002	-0.055	0.051	-0.028
			(0.013)	(0.015)	(0.016)	(0.015)	(0.015)	(0.014)
			(-0.705, 0.420)	(-0.686, 0.469)	(-0.608, 0.518)	(-0.747, 0.517)	(-0.495, 0.586)	(-0.591, 0.490)
Amount < 2.5b					-0.221	-0.228	-0.287	-0.305
					(0.009)	(0.010)	(0.007)	(0.009)
					(-0.578, 0.121)	(-0.550, 0.085)	(-0.645, 0.065)	(-0.649, 0.036)
Post 2012					-0.113	-0.166	-0.117	-0.152
					(0.011)	(0.011)	(0.011)	(0.011)
					(-0.571, 0.287)	(-0.587, 0.213)	(-0.544, 0.292)	(-0.586, 0.266)
Amount < 2.5b × Post 2012					0.246	0.029	-0.123**	-0.116**
					(0.011)	(0.010)	(0.002)	(0.002)
					(-0.178, 0.656)	(-0.338, 0.400)	(-0.209, -0.042)	(-0.199, -0.024)
Ln(Institutional Demand)							-0.482**	-0.512**
							(0.008)	(0.007)
							(-0.822, -0.176)	(-0.830, -0.160)
Pre-commitment							0.352	0.048
							(0.011)	(0.010)
							(-0.084, 0.753)	(-0.353, 0.418)
Ln(Institutional Demand) × Pre-commitment							0.049	0.038
							(0.003)	(0.009)
							(-0.078, 0.182)	(-0.345, 0.379)
Year FE	No	No	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes	Yes	Yes
Number of Obs.	226	226	226	226	226	226	226	226

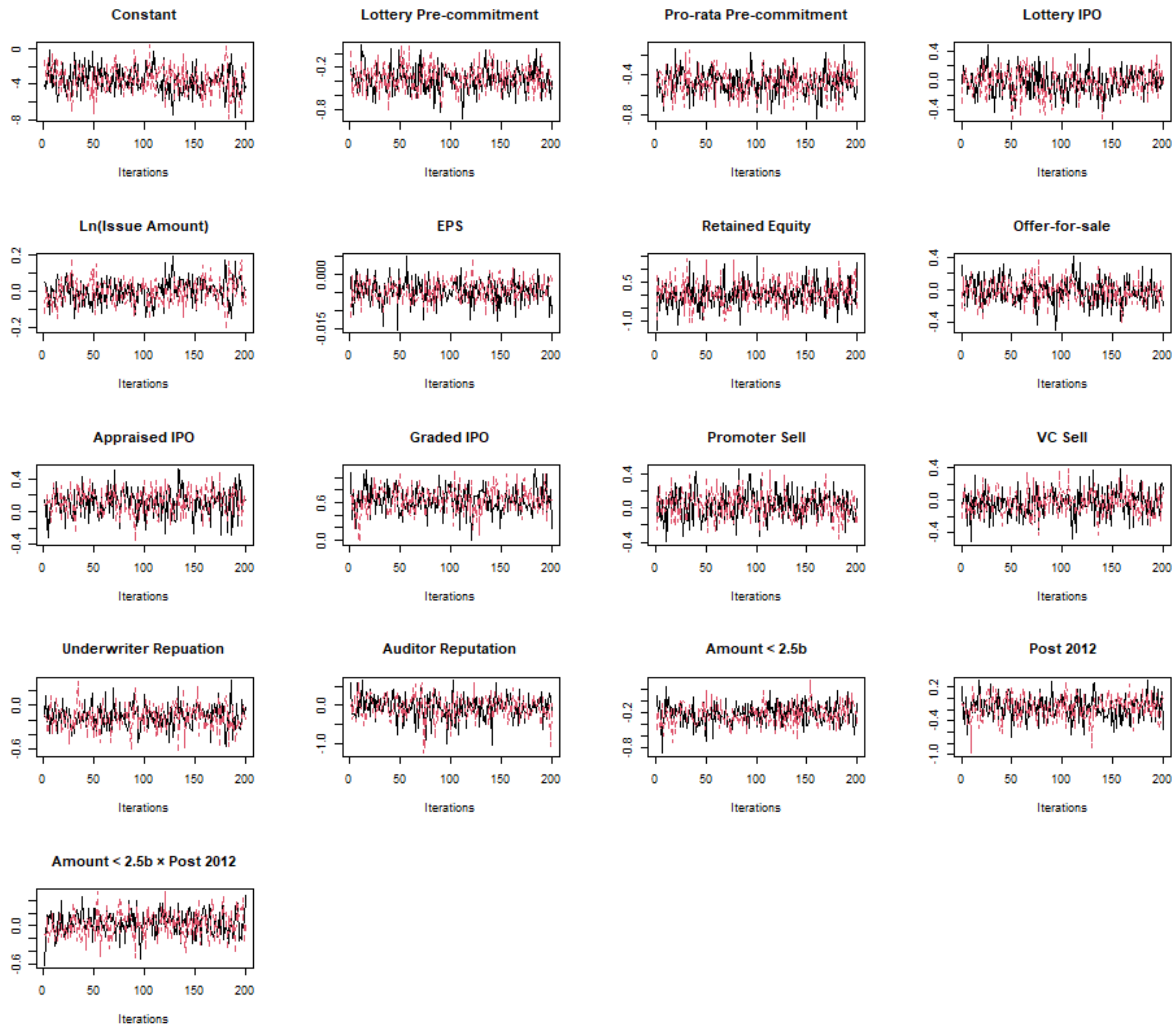

Figure B1. Trace plots for the zero-inflated beta regression Model 6 in Table B1.

Table B2: This table shows the summary statistics of the variables used in the analysis by lottery pre-commitment and pro-rata pre-commitment. The dataset consists of 417 IPOs in India between November 2005 and March 2019. The variables shown in the table are defined in Appendix A.

Number of IPOs and mean, median, and standard deviation of IPO characteristics by lottery pre-commitment and pro-rata pre-commitment.

	Lottery No Pre-commitment			Lottery Yes Pre-commitment			Pro-rata No Pre-commitment			Pro-rata Yes Pre-commitment		
Number of IPOs	(96)			(43)			(183)			(95)		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Price Volatility	0.031	0.03	0.012	0.019	0.019	0.007	0.036	0.033	0.016	0.020	0.018	0.009
Issue-price Update	0.062	0.064	0.021	0.023	0.016	0.020	0.051	0.048	0.026	0.023	0.018	0.020
Underpricing	0.476	0.402	0.449	0.332	0.305	0.253	0.08	-0.016	0.388	0.020	0.000	0.149
Ln(Issue Amount)	21.577	21.244	1.295	22.466	22.309	0.897	20.806	20.524	1.152	22.435	22.353	1.047
Ln(Institutional Demand)	3.925	3.987	0.658	3.432	3.438	0.474	0.539	0.429	1.308	1.166	0.957	0.758
Ln(Retail Demand)	2.655	2.637	0.907	1.942	2.048	0.896	0.839	0.912	1.167	0.239	0.262	1.310
EPS	11.274	8.77	17.146	16.464	9.69	26.128	12.138	6.42	37.676	8.075	6.920	14.960
Retained Equity	0.798	0.8	0.086	0.857	0.876	0.072	0.693	0.714	0.124	0.806	0.802	0.091

Table B3: This table shows the descriptive statistics of the variables used in the analysis by year. The dataset consists of 417 IPOs in India in India between November 2005 and March 2019. The variables are defined in Appendix A.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Number of IPOs	11	58	87	35	15	62	30	9	3	5	20	24	32	24	2
								Mean							
Price Volatility	0.029	0.031	0.034	0.044	0.026	0.026	0.042	0.023	0.020	0.028	0.022	0.019	0.018	0.019	0.026
Issue-price Update	0.065	0.066	0.062	0.047	0.041	0.039	0.043	0.039	0.031	0.034	0.029	0.026	0.012	0.009	0.020
Underpricing	0.252	0.270	0.298	0.153	0.111	0.127	0.101	0.030	0.022	0.261	0.088	0.131	0.188	0.075	-0.036
Ln(Issue Amount)	20.866	20.970	21.102	20.908	21.518	21.554	20.804	21.710	21.775	21.517	22.276	22.536	22.925	22.856	21.388
Ln(Institutional Demand)	2.777	2.578	2.454	1.035	0.890	1.501	-0.390	1.297	1.095	2.213	1.410	1.713	2.190	1.770	0.721
Ln(Retail Demand)	2.507	1.842	1.750	0.790	0.348	0.987	1.086	0.378	0.050	2.283	0.280	1.031	1.491	0.470	-1.537
EPS	13.949	8.597	12.832	19.894	12.333	11.739	5.991	11.921	8.247	11.508	9.126	12.536	8.584	15.393	-47.840
Retained Equity	0.738	0.734	0.747	0.738	0.753	0.746	0.676	0.783	0.828	0.780	0.821	0.831	0.827	0.826	0.729
								Median							
Price Volatility	0.029	0.029	0.032	0.043	0.020	0.022	0.039	0.022	0.022	0.028	0.021	0.019	0.015	0.018	0.026
Issue-price Update	0.067	0.076	0.064	0.044	0.034	0.035	0.045	0.038	0.024	0.037	0.022	0.016	0.009	0.007	0.020
Underpricing	0.261	0.187	0.150	0.024	0.023	0.087	0.007	0.001	-0.023	0.261	0.026	0.136	0.032	0.000	-0.036
Ln(Issue Amount)	20.713	20.820	20.733	20.577	20.854	21.366	20.591	21.308	21.717	21.403	22.313	22.445	22.652	22.969	21.388
Ln(Institutional Demand)	2.598	2.744	2.636	0.795	0.075	1.290	-0.248	1.349	0.955	2.487	0.904	1.628	1.824	1.629	0.721
Ln(Retail Demand)	2.503	1.867	1.708	0.713	0.548	1.155	1.048	0.470	-0.315	1.991	0.329	0.739	1.753	0.274	-1.537
EPS	8.490	6.280	8.440	6.450	9.140	7.130	3.620	8.490	5.910	10.310	6.845	10.690	7.465	9.520	-47.840
Retained Equity	0.725	0.743	0.749	0.742	0.754	0.779	0.727	0.806	0.846	0.748	0.843	0.846	0.849	0.862	0.729
								SD							
Price Volatility	0.008	0.010	0.012	0.018	0.017	0.014	0.018	0.010	0.003	0.008	0.008	0.008	0.010	0.009	0.016
Issue-price Update	0.018	0.025	0.023	0.025	0.026	0.018	0.023	0.030	0.014	0.013	0.019	0.024	0.011	0.007	0.016
Underpricing	0.209	0.426	0.523	0.436	0.364	0.279	0.507	0.122	0.116	0.329	0.188	0.203	0.344	0.231	0.103
Ln(Issue Amount)	1.000	0.935	1.244	1.331	1.672	1.240	0.972	1.300	1.139	0.462	0.815	0.916	1.217	0.990	3.018
Ln(Institutional Demand)	0.903	1.253	1.923	1.830	1.771	1.819	1.312	1.066	0.780	0.764	1.249	1.157	1.522	1.356	0.284
Ln(Retail Demand)	0.524	1.035	1.484	1.515	1.017	1.589	1.089	1.378	1.037	0.797	0.944	1.024	1.283	1.464	3.358
EPS	12.420	11.851	36.834	64.022	22.631	22.154	8.890	11.686	4.125	8.597	14.964	12.087	9.471	13.995	70.583

Retained Equity	0.096	0.104	0.130	0.126	0.122	0.128	0.113	0.144	0.074	0.066	0.081	0.091	0.093	0.104	0.022

Table B4: This table presents the results of beta regressions with issue-price update as the dependent variable and lottery pre-commitment and pro-rata pre-commitment as the key independents. The reference category is pro-rata IPOs with no pre-commitment from institutional investors. The dataset consists of 412 IPOs in India between November 2005 and March 2019 (five IPOs with issue-price update equal to zero are excluded). Robust standard errors are reported in brackets. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively. All variables are defined in Appendix A.

	Issue-price Update (Beta Regressions)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-2.914***	-2.740***	-2.176***	-3.908***	-1.485*	-1.624*	-1.599*	-1.731*
	(0.041)	(0.058)	(0.588)	(0.550)	(0.898)	(0.897)	(0.898)	(0.897)
Lottery Pre-commitment	-1.106***	-0.593***	-0.958***	-0.592***	-0.546***	-0.535***		
	(0.121)	(0.115)	(0.125)	(0.118)	(0.130)	(0.129)		
Pro-rata Pre-commitment	-0.894***	-0.639***	-0.685***	-0.639***	-0.432***	-0.446***		
	(0.085)	(0.083)	(0.097)	(0.092)	(0.104)	(0.103)		
Lottery IPO	0.226***	0.096	0.276***	0.109*	0.161**	0.130*	0.252***	0.218**
	(0.063)	(0.059)	(0.071)	(0.065)	(0.068)	(0.068)	(0.094)	(0.095)
Ln(Issue Amount)			-0.036	0.062**	-0.047	-0.038	-0.043	-0.035
			(0.030)	(0.028)	(0.041)	(0.041)	(0.041)	(0.041)
EPS			-0.001	-0.0004	-0.0004	-0.0001	-0.0003	-0.0001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Retained Equity			-0.001	-0.213	-0.183	-0.214	-0.032	-0.072
			(0.296)	(0.269)	(0.279)	(0.281)	(0.293)	(0.295)
Offer-for-sale			-0.295***	-0.043	-0.010	-0.011	-0.028	-0.027
			(0.101)	(0.091)	(0.100)	(0.100)	(0.100)	(0.101)
Appraised IPO			0.194**	0.199***	0.161**	0.169**	0.152**	0.162**
			(0.080)	(0.073)	(0.076)	(0.077)	(0.076)	(0.077)
Graded IPO			0.003	0.003	-0.194***	-0.206***	-0.227***	-0.239***
			(0.058)	(0.087)	(0.060)	(0.061)	(0.063)	(0.063)
Promoter Sell			-0.024	0.026	-0.127	-0.148	-0.117	-0.141
			(0.129)	(0.115)	(0.123)	(0.124)	(0.123)	(0.124)

VC Sell			0.168	-0.016	0.004	-0.019	0.0003	-0.024
			(0.128)	(0.113)	(0.122)	(0.122)	(0.123)	(0.122)
Underwriter Reputation			0.136	-0.058	0.044	0.034	0.045	0.037
			(0.084)	(0.076)	(0.079)	(0.080)	(0.079)	(0.080)
Auditor Reputation			0.065	0.141	0.170	0.102	0.180	0.112
			(0.163)	(0.147)	(0.155)	(0.156)	(0.155)	(0.156)
Amount < 2.5b					-0.261**	-0.286***	-0.269**	-0.293***
					(0.106)	(0.107)	(0.106)	(0.107)
Post 2012					-0.959***	-0.987***	-0.982***	-1.012***
					(0.123)	(0.124)	(0.125)	(0.126)
Amount < 2.5b × Post 2012					0.646***	0.697***	0.678***	0.729***
					(0.165)	(0.167)	(0.167)	(0.169)
Ln(Institutional Demand)							-0.041	-0.040
							(0.027)	(0.027)
Pre-commitment							-0.416***	-0.441***
							(0.129)	(0.129)
Ln(Institutional Demand) × Pre-commitment							-0.029	-0.017
							(0.050)	(0.049)
Year FE	No	Yes	No	Yes	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Number of Obs.	412	412	412	412	412	412	412	412
Pseudo R^2	0.351	0.586	0.403	0.597	0.466	0.474	0.466	0.473
φ	63.53	90.35	68.97	93.36	79.86	81.47	80.34	81.92
RMSE	0.023	0.020	0.022	0.020	0.021	0.020	0.020	0.020

*p<0.1; **p<0.05; ***p<0.01

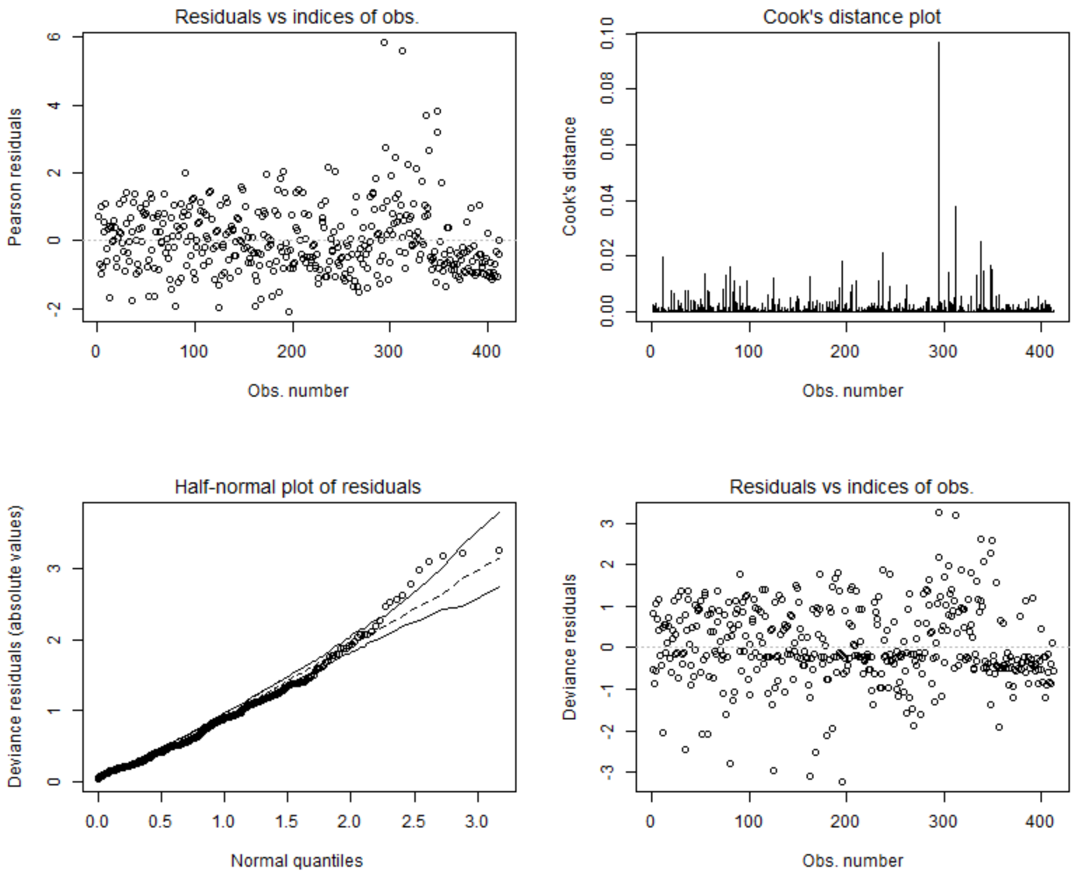

Figure B2. Diagnostic plots for the beta regression Model 6 in Table B2. The upper left panel is the plot of Pearson residuals versus the number of observations, the upper right panel is the Cook's distance versus the number of observations, the lower left panel displays the half-normal plot of absolute deviance residuals with simulated envelope, the lower right panel is the plot of deviance residuals versus the number of observations.

Table B5

This table reports the results of beta regressions with price volatility as the dependent variable and issue-price update, lottery pre-commitment, pro-rata pre-commitment, pro-rata IPOs, and their interaction terms, as the key independent variables. The reference category is pro-rata IPOs with no pre-commitment from institutional investors. The dataset consists of 417 IPOs in India between November 2005 and March 2019. All variables are defined in Appendix A. Robust standard errors are reported in brackets. ***, **, and * indicate significant at the 1%, 5%, and 10% level, respectively.

	Price Volatility (Beta Regressions)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Constant	-3.330***	-0.056	0.065	-0.109	-0.147	-0.102	-0.320	-0.278	-0.338	-0.308	-0.163	-0.117	-0.207	-0.174
	(0.056)	(0.426)	(0.466)	(0.478)	(0.687)	(0.684)	(0.704)	(0.702)	(0.700)	(0.697)	(0.687)	(0.683)	(0.683)	(0.680)
Issue-price update	0.320	-0.536	-0.623	-0.670	-0.516	-0.492	0.616	0.693	0.633	0.719	-0.753	-0.657	-0.720	-0.616
	(0.942)	(0.829)	(0.839)	(0.834)	(0.863)	(0.857)	(0.792)	(0.788)	(0.788)	(0.785)	(1.027)	(1.020)	(1.025)	(1.019)
Lottery Pre-commitment	-0.376***	-0.172	-0.197	-0.167	-0.207	-0.240*								
	(0.133)	(0.120)	(0.120)	(0.121)	(0.127)	(0.126)								
Pro-rata Pre-commitment	-0.684***	-0.312***	-0.363***	-0.291***	-0.370***	-0.369***								
	(0.095)	(0.090)	(0.091)	(0.092)	(0.097)	(0.096)								
Issue-price update × Lottery Pre-commitment	-1.182	-1.410	-2.791	-1.486	-2.659	-2.021								
	(3.907)	(3.470)	(3.563)	(3.443)	(3.576)	(3.507)								
Issue-price update × Pro-rata Pre-commitment	6.639***	5.579**	5.402**	5.345**	5.436**	5.256**								
	(2.537)	(2.217)	(2.280)	(2.228)	(2.279)	(2.259)								
Lottery IPO	-0.132**	0.031	0.029	0.041	0.029	0.042	0.013	0.022			0.033	0.045		
	(0.051)	(0.072)	(0.073)	(0.071)	(0.073)	(0.073)	(0.067)	(0.067)			(0.068)	(0.068)		
Underpricing		0.220***	0.240***	0.225***	0.239***	0.238***	0.239***	0.233***	0.240***	0.234***	0.237***	0.237***	0.238***	0.239***
		(0.043)	(0.044)	(0.043)	(0.045)	(0.045)	(0.046)	(0.046)	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)	(0.045)
Ln(Issue Amount)		-0.161***	-0.163***	-0.153***	-0.155***	-0.157***	-0.149***	-0.151***	-0.149***	-0.150***	-0.154***	-0.156***	-0.152***	-0.154***
		(0.020)	(0.022)	(0.023)	(0.031)	(0.031)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Ln(Institutional Demand)		-0.025	-0.029	-0.018	-0.027	-0.028	-0.032	-0.032	-0.030*	-0.029*	-0.035	-0.032	-0.031	-0.026
		(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.017)	(0.017)	(0.032)	(0.032)	(0.031)	(0.031)
Pre-commitment											-0.353***	-0.338***	-0.360***	-0.348***
											(0.125)	(0.124)	(0.124)	(0.123)
Ln(Retail Demand)		-0.010	-0.013	-0.014	-0.013	-0.017	-0.008	-0.011	-0.006	-0.010	-0.012	-0.016	-0.009	-0.013
		(0.019)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
EPS			0.0002	-0.0002	0.0002	-0.00000	0.0001	-0.0001	0.0001	-0.0001	0.0002	0.00005	0.0002	0.00004
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Retained Equity			0.011	-0.155	0.017	-0.032	-0.039	-0.088	-0.040	-0.089	0.006	-0.045	0.005	-0.048
			(0.195)	(0.189)	(0.196)	(0.195)	(0.200)	(0.199)	(0.200)	(0.199)	(0.197)	(0.196)	(0.197)	(0.196)
Offer-for-sale			-0.114*	-0.087	-0.123*	-0.131*	-0.128*	-0.133*	-0.127*	-0.132*	-0.132*	-0.140**	-0.131*	-0.139**
			(0.065)	(0.065)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Appraised IPO			0.002	0.035	0.004	0.020	-0.007	0.007	-0.008	0.006	0.009	0.024	0.008	0.023

			(0.053)	(0.052)	(0.053)	(0.053)	(0.054)	(0.055)	(0.054)	(0.055)	(0.053)	(0.054)	(0.053)	(0.054)
Graded IPO			0.078**	0.052	0.086*	0.090**	0.056	0.059	0.057	0.060	0.095**	0.100**	0.095**	0.101**
			(0.040)	(0.062)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)
Promoter Sell			0.042	0.036	0.049	0.056	0.061	0.073	0.062	0.073	0.058	0.067	0.058	0.067
			(0.081)	(0.079)	(0.082)	(0.082)	(0.083)	(0.083)	(0.083)	(0.083)	(0.082)	(0.082)	(0.082)	(0.082)
VC Sell			0.026	0.035	0.033	0.046	-0.014	-0.001	-0.014	-0.0005	0.043	0.057	0.042	0.057
			(0.079)	(0.076)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
Underwriter Reputation			0.058	0.041	0.059	0.043	0.046	0.034	0.046	0.033	0.054	0.038	0.052	0.036
			(0.059)	(0.058)	(0.059)	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Auditor Reputation			-0.179	-0.174	-0.188	-0.198	-0.184	-0.178	-0.184	-0.180	-0.183	-0.192	-0.185	-0.195
			(0.122)	(0.119)	(0.123)	(0.124)	(0.126)	(0.126)	(0.126)	(0.126)	(0.124)	(0.124)	(0.123)	(0.124)
Amount < 2.5b					0.036	0.042	0.083	0.097	0.083	0.098	0.042	0.048	0.043	0.049
					(0.077)	(0.077)	(0.078)	(0.078)	(0.078)	(0.078)	(0.077)	(0.077)	(0.077)	(0.077)
Post 2012					0.036	0.072	-0.091	-0.062	-0.091	-0.063	0.050	0.087	0.048	0.084
					(0.087)	(0.087)	(0.082)	(0.082)	(0.082)	(0.082)	(0.088)	(0.088)	(0.088)	(0.088)
Amount < 2.5b × Post 2012					-0.017	-0.058	-0.004	-0.043	-0.006	-0.045	-0.036	-0.081	-0.036	-0.080
					(0.105)	(0.106)	(0.105)	(0.106)	(0.105)	(0.106)	(0.106)	(0.108)	(0.106)	(0.108)
Issue-price update × Ln(Institutional Demand)											0.199	0.143	0.209	0.158
											(0.451)	(0.447)	(0.451)	(0.448)
Issue-price update × Pre-commitment											6.795**	6.473**	6.826**	6.515**
											(3.003)	(2.972)	(3.005)	(2.976)
Ln(Institutional Demand) × Pre-commitment											0.025	0.011	0.029	0.017
											(0.052)	(0.052)	(0.052)	(0.051)
Issue-price update × Ln(Institutional Demand) × Pre-commitment											-2.333*	-2.106	-2.359*	-2.148
											(1.399)	(1.378)	(1.400)	(1.379)
Year FE	No	Yes	No	Yes	No	No	No	No	No	No	No	No	No	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of Obs.	417	417	417	417	417	417	417	417	417	417	417	417	417	417
Pseudo R^2	0.282	0.560	0.512	0.569	0.513	0.522	0.485	0.496	0.485	0.495	0.511	0.522	0.511	0.521
φ	186.62	309.20	278.28	314.80	278.51	285.17	264.68	270.92	264.66	270.85	278.48	285.62	278.33	285.33
RMSE	0.013	0.010	0.011	0.010	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.001	0.011

*p<0.1; **p<0.05; ***p<0.01

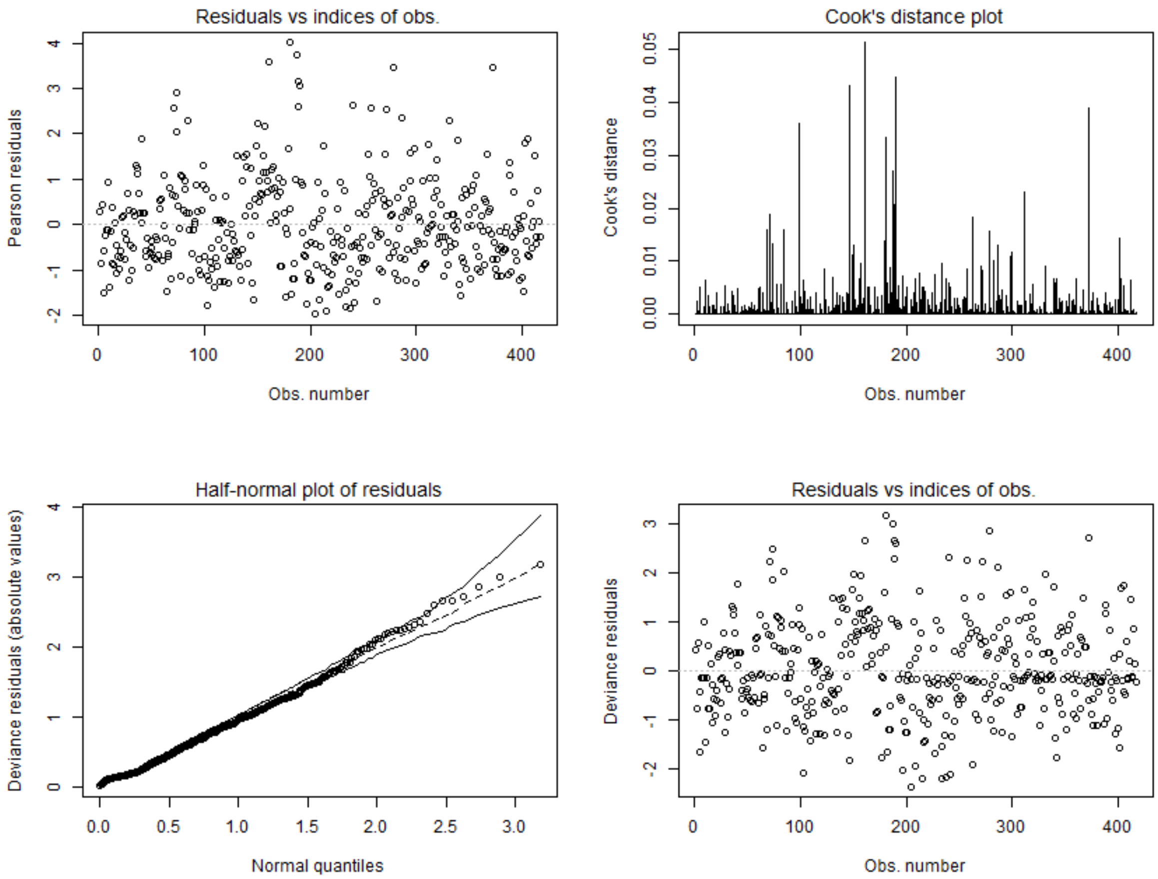

Figure B3. Diagnostic plots for the beta regression Model 6 in Table B5. The upper left panel is the plot of Pearson residuals versus the number of observations, the upper right panel is the Cook's distance versus the number of observations, the lower left panel displays the half-normal plot of absolute deviance residuals with simulated envelope, the lower right panel is the plot of deviance residuals versus the number of observations.