Pre-Opening Trading, Price Limits, and the Volatility of IPO Initial Returns

Aarti Sharma
IILM Institute for Higher Education
New Delhi, India
Email: aartisharmaphd@gmail.com

Vishwanatha S R
Shiv Nadar University
Delhi NCR, India
Email: srvishy@gmail.com

Abstract

In 2012 the Securities Exchange Board of India introduced a rule mandating a pre-opening trading session for IPOs on the listing day and price limits during the first ten days of trading. We use this natural experiment to test whether the secondary market structure affects the level and volatility of IPO initial returns. We document a significant reduction in volatility after controlling for market-wide volatility. The reduction is also significant for younger firms and hard-to-place offerings that face asymmetric information and valuation uncertainty. Our results suggest that regulatory price limits are useful in curbing the volatility of IPO initial returns.

JEL Classification: G14, G 18, G24, G32

Keywords: Market Microstructure, Financial Market Policy, IPO, Corporate Finance

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1. Introduction

Most firms that go public through an initial public offering of shares are underpriced[1]. The average underpricing in the U.S. has been 18% during 1980-2019[2]. This phenomenon has been the subject of much scholarly debate over the last few decades (See Ritter, 1984 a, b; Beatty and Ritter, 1986; Ritter, 1994; Ibbotson et al, 1988, 1994; Loughran and Ritter, 1995; Loughran and Ritter, 2004 and Ljungqvist, 2007 for a survey of the empirical evidence and theories of underpricing). This study uses a natural experiment resulting from the 2012 Securities Exchange Board of India rule mandating a change in the structure of trading of IPOs on the listing day for all stocks listed on the BSE (Bombay Stock Exchange) and NSE (National Stock Exchange) to test whether the secondary market structure affects the mean and volatility of underpricing of IPOs. In 2012 the Securities Exchange Board of India (SEBI) introduced a call auction mechanism for freshly listed IPOs. Under the law that came into effect on January 20th, there is a pre-trading session before the normal trading begins. The pre-trading session has a duration of 60 minutes from 9:00 A.M to 10:00 A.M. This session is conducted for IPOs only on the day of the listing on the stock exchange. This pre-market session is expected to result in improved price discovery in the normal trading session that follows. Pre-opening sessions are available on the National Stock Exchange of India (NSE) and the Bombay Stock Exchange (BSE). We conjecture that the pre-opening trading on the first day of listing could result in lower underpricing of IPOs because of improved price discovery. Further, guidelines by SEBI impose trading controls and allow prices of freshly listed firms to

[1] Underpricing is the percentage difference between the issue price and the closing price on the listing day. A positive initial return is known as underpricing, whilst a negative initial return is known as overpricing. (Ibbotson et al, 1988; Ritter, 1998). The term "initial return" also refers to underpricing.

[2] https://site.warrington.ufl.edu/ritter/files/2020/01/IPOs2019Statistics_Jan14_2020.pdf accessed on February 13, 2020

fluctuate within specified price bands for 10 days after listing. SEBI guidelines require that in the normal trading session the prices of IPO firms fluctuate within a price band of ±5% of the equilibrium price[3] for IPOs with proceeds less than INR 2.5b and ±20% of the equilibrium price for IPOs with proceeds more than INR 2.5b. This feature could potentially reduce the volatility of IPO initial returns. In the U.S, IPOs listed on NASDAQ have a pre-opening period that lasts for a maximum of five minutes before actual trading begins (Aggarwal and Conroy, 2010). The Indian system provides a longer, one hour, time window for investors to trade. One of the purported advantages of a call auction market is the reduced initial return volatility due to multiple matching of orders at a single price. Thus, the Indian experiment addresses not only the absolute level of initial returns but also its volatility. Price support in the form of price limits may mitigate adverse selection problems in the IPO market.

By studying this natural experiment, we contribute to the IPO literature in several ways. Our study is mainly motivated by Lowry, Officer and Schwert (2010, LOS hereafter), who document substantial volatility in IPO initial returns (34%) in the U.S. They propose the use of volatility of initial returns as a new metric to evaluate the efficacy of pricing of IPOs. Because they observe extreme variability in initial returns, they suggest that alternate mechanisms such as auctions could result in better price discovery. They find that firms with greater uncertainty have higher volatility and the underwriters' pricing problem is also sensitive to market conditions.

Ruud (1993) too investigates the distribution of initial returns. She shows that the high initial return need not be deliberate underpricing but could be due to price stabilization undertaken by the underwriters. In other words, price stabilization may result in underpricing. IPO price stabilization by underwriters is not popular in India. Therefore, price stabilization by controlled trading is more

[3] The clearing price at which orders are matched and executed.

valuable. In this paper we study an experiment that could potentially reduce the volatility of initial returns.

This research is also motivated by the concern of stock exchanges, regulators, and market participants about the volatility of initial returns of IPOs. The initial trading in these stocks can be noisy and has become a cause for concern. For example, Facebook, a social networking company's stock fell below the IPO price and the investment banks had to buy shares in the market to stabilize the price. This phenomenon is not unique to Facebook or the U.S.A. Underpricing in emerging markets such as India is not only much higher than the developed markets but is also more volatile. For instance, initial return in India was 88% during 1990-2014 and in China it was 113.5% during the same period [4]. Furthermore, it has varied considerably through the 80s, 90s and the 2000s. The IPO initial returns are substantially volatile and larger during "hot" IPO markets. They also fluctuate dramatically over time (Ibbotson et al, 1988; Ritter, 1984; Lowry et al, 2010). The aforementioned regulatory interference in India is in response to widespread underpricing and volatility in initial returns.

Uncertain prospects of equity in private firms make it inherently difficult to value thereby leading to underpricing as an efficient response to the complexity of this valuation problem (Rock, 1986; Beatty and Ritter, 1986; Benveniste and Spindt, 1989; Ritter and Welch, 2002; Lowry et al, 2010). The volatility of initial returns is higher for firms that are more difficult to value because of higher information asymmetry (Rock, 1986). Smaller firms, younger firms and firms facing valuation uncertainty are particularly difficult to value because they are new or not well understood by the market participants and suffer from asymmetric information ((Ritter, 1984; Clarkson and

[4] https://site.warrington.ufl.edu/ritter/files/2015/05/Initial-Public-Offerings-International-Insights-2015-05-21.pdf , accessed on February 13, 2020.

Merkley, 1994; Lowry et al, 2010). Since the objective of the new trading mechanism in India is to reduce the overall level of underpricing and its volatility, we test whether this is achieved after controlling for a variety of IPO and firm related variables that are known to affect underpricing and price volatility. In addition, we also study the impact of price limits and pre-opening trading on firms facing asymmetric information and valuation uncertainty. A key contribution of this paper is that by studying the institutional mechanism in an emerging market we provide a direct test of how regulators can curb excessive volatility of freshly listed IPO returns.

Prior to this experiment, the Securities Exchange Board of India, on July 9, 2009, allowed a two-stage IPO process in which qualified institutional investors were allowed to act as anchor investors (or lead investors) in IPOs (Seth et al, 2019; Bhattacharya et al, 2020). Anchor investors are allotted shares on a discretionary basis and the price at which allocation is made is disclosed by the lead investment bank one day before the opening of the offer to the public[5]. If the bidding by anchor investors results in a higher offer price later, then all investors, including the anchors, pay the higher price. These investors face a short lock-up period of 30 days from the date of allotment. Thus, the Indian IPO process is a sequential hybrid mechanism in which anchor investors lead the price setting process. The Indian experiment is consistent with Jagannathan and Sherman (2005) who suggest modifying the book building method in order to retain its advantages (vis-à-vis auctions) while at the same time making it transparent and encouraging retail participation. The National Stock Exchange and Bombay Stock Exchange have nationwide trading network and conduct online IPOs. The process allows investors to observe bids made by different classes of investors. This makes the book building process transparent. However, investors do not

[5] In other countries, institutional investors are allocated shares along with other classes of investors such as retail investors once the book is closed.

witness how many anchor investors wanted to participate and their bids. Seth et al, (2019) find that anchor investors are more likely to invest in smaller firms facing valuation uncertainty and that these IPOs are less likely to be priced at the upper end of the price band. They find that these firms are less profitable and take longer to go public. That is, anchor backed IPOs are hard-to-place offerings. They document a negative, causal relation between allocation to anchor investors and underpricing. Since anchor backed IPOs suffer from valuation uncertainty, we posit that the introduction of price limits may further reduce the volatility of underpricing of these IPOs in particular. That is, we take anchor backing as proxy for asymmetric information and uncertainty.

Daily price limits are common in many stock markets around the world (Deb et al, 2010). Price limits are boundaries that specify the maximum range within which security prices are allowed to move within a single day. They are intended to reduce stock market volatility but many academics (e.g., Fama, 1989; Kim, 2001, Lin, 2009) argue that price limits may actually increase stock market volatility due to spill over on subsequent days and prevent prices from reaching their equilibrium level. Kim and Rhee (1997) show that price limits may be ineffective. However, Deb et al, (2010) argue that if the cost of monitoring a market (due to poor business disclosure, corruption and less efficiency in legal and regulatory oversight) is high, price-limit rules are beneficial. Further, price limits mitigate abnormal trading activity and curb volatility of poorly performing stocks (Kim et al, 2013). We contribute to this strand of literature by examining the impact of trading controls in the context of emerging market IPOs that are prone to excessive volatility in the initial days of trading.

In several countries the underwriter(s) stands ready to buy back shares at the offer price to compensate investors for adverse selection they face in bidding for IPOs (Hanley et al, 1993; Lewellen, 2003). One way to compensate investors is to allow underpricing of IPOs. But underpricing is expensive for issuing firms. Stabilization raises the equilibrium stock price. Price discovery and stabilization by the trading mechanism takes the pressure off the issuing firm to appoint underwriters to provide price stabilization activities. More importantly, it solves the tension between price manipulation and channeling of capital to certain industries (by stabilizing IPO prices) inherent in stabilization activities of underwriters (Prabhala and Puri, 1998)[6]. Our setting also allows us to study who benefits more from the legally mandated price discovery and support. Specifically, we examine whether riskier firms benefit more[7]. This is particularly important for such firms because reputed underwriters may be unwilling to support riskier firms or when the market is cold. As pointed out earlier, price stabilization by underwriters is not popular in India. Therefore, price stabilization by regulated trading is more valuable[8].

Several authors such as Derrien (2005), Ljungqvist (2006), and Clarke et al, (2016) suggest that investors' sentiment drive an IPO's first day returns. Pre-IPO markets where investors trade before the IPO firm gets listed, exist in several countries. Studies of European grey markets and India suggest that pre-market prices are informative about post-market prices (Löffler et al, 2005; Aussenegg, et al, 2006; Derrien and Kecskés, 2007; Brooks et al, 2014), Cornelli et al, (2006) document irrational behaviour among investors in the context of grey market traders in Europe. Our paper focuses on exchange trades on the listing day, not grey markets. And we do not study bidding behaviour of investors. Chang et al, (2014) study Taiwan's Emerging Stock Market where firms are required to trade on an exchange for six months before they apply for an IPO. We study

[6] Aggarwal (2010) observes that underwriters rarely resort to stabilizing bids because they send negative signal to investors about the demand for the stock. To the extent that preopening orders can be cancelled, traders can use them to manipulate the market. That is, preopening trading is not entirely free from manipulation.

[7] We use firm age and anchor backing as proxies for uncertainty.

[8] As LOS show, volatility of initial returns is high in the U.S. where underwriters often post stabilizing bids in the after-market.

the broader implications of the trading mechanism on the IPO process, not bids by traders on the opening day. They study pre-market prices *before* the IPO. Our paper is related to theirs in that we too study the informativeness of the pre-market price in predicting the after-market price. To the extent that more recent trades are more informative than trades that took place a few days or months ago, we would expect the results to be stronger in our setting.

Papers that study trading systems in the U.S.A. test whether the secondary market structure affects IPO underpricing. Ligon and Liu (2011) study the 1997 Securities and Exchange Commission rule mandating a change in the order handling rules for all NASDAQ stocks to examine its impact on underpricing. In 1997 the SEC mandated the rule for all NASDAQ issues requiring a limit order to be posted on the trading system if it improves a dealer's quotes. Thus, the rule allows limit orders to compete directly with dealer quotes. They find that the rule led to an increase in liquidity of the market and a decrease in underpricing of cold issues. This result is consistent with Ellul and Pagano (2006) who argue that the required returns of investors adjust in response to expected liquidity in the secondary market. The lower the expected liquidity in the secondary market, the higher is the expected initial return. Graves et al, (1993) study how the choice of trading location i.e., stock exchange (NYSE, AMEX, and NASDAQ) affects underpricing. They find that underpricing is prevalent in all exchanges but through quantitative and quantitative listing standards, trading systems certify the quality of IPOs. The higher listing standards of certain exchanges reduces the ex-ante uncertainty about the value of an IPO and therefore, its underpricing. We add to this literature by examining the impact of trading controls on the variability of IPO initial returns.

Since our paper is mainly motivated by LOS, our research design is similar to theirs. We analyze the absolute level and volatility of IPO initial returns using Ordinary Least Square (OLS) regressions and Maximum Likelihood Estimation (MLE) before and after the introduction of the regulation. We examine whether firms that face asymmetric information or uncertainty (e.g., younger firms, anchor backed IPOs) experience lower volatility after 2012 using OLS, propensity score matching and difference and difference estimation. Naturally, IPO underpricing tends to be more volatile when secondary markets are volatile. We investigate the effect of price limits after adjusting for market volatility. We present graphical and econometric evidence throughout our paper. Our main result is that there is a significant, overall, reduction in initial returns and volatility after controlling for investor demand, offer and firm characteristics after the introduction of the price limits. For a median IPO in our sample, the volatility of 21-day initial returns declined by 32%, without adjusting for firm characteristics. A maximum likelihood estimation of volatility indicates that it declined by 4.27% for all IPOs. Firms that face greater asymmetric information and hard to place offerings too experienced a drop in volatility after the introduction of the new legislation. We use anchor backing and firm age as instruments to identify firms that face asymmetric information and valuation uncertainty. A difference-in-difference estimation shows that volatility of anchor backed IPOs fell by 17.39%. Over a five-year window surrounding the new regulation, volatility of young firms fell by 8.24%. Our findings are generally robust to alternate econometric methodologies such as multivariate regressions, MLE, propensity score matching and difference-in-difference estimation. The rest of the paper proceeds as follows. In Section 2 we describe the institutional setting, data sources, sample selection, variable construction and descriptive statistics. In Section 3 we present the empirical results. Section 4 presents the summary of our findings and conclusion.

2. Institutional Setting, Data and Sample

2.1.Institutional Setting

The goal of every IPO mechanism is to specify rules relating to bidding and allocations that provide an incentive to disclose information, minimize costs to investors and produce a fair price in the after-market (Bubna and Prabhala, 2014). The book building process in India is similar to that in the U.S. and other developed markets. In India, each IPO is offered to three categories of investors: retail, non-institutional and qualified institutional buyers (QIB) or institutional investors[9]. The Indian securities law prescribes that (a) not less than 30% of the net offer be allotted to retail individual investors; (b) not less than 10% of the net offer be allotted to non-institutional investors i.e., investors other than retail individual investors and Qualified Institutional Buyers; and (c) not more than 60% of the net offer be allotted to Qualified Institutional Buyers. If QIBs apply for exactly the same number of shares ear marked for them, the offer would have a subscription of 1x in the QIB category. Thus, a QIB subscription of 10x implies an oversubscription of 9x in the QIB category. Over the years, there have been variants of book building in the Indian market. For instance, in November 2005, the underwriters' powers over IPO allocations were withdrawn even in book-built IPOs (Bubna and Prabhala, 2011).

The Securities & Exchange Board of India allowed qualified institutional investors to act as anchor (lead) investors in initial public offerings in order to boost investor confidence in IPOs[10].This legislation came into effect on July 9, 2009. Earlier laws required that pre-IPO placement of shares to other investors such as hedge funds and private equity funds be locked-up for one year, which prohibited investors from exiting. Further, issuers were compelled to issue shares at a discount to compensate investors for illiquidity. Under the regulation, a company can allocate a maximum of thirty percent of the QIB section to anchor investors. The minimum

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[9]Qualified institutional investors are institutional investors who are generally perceived to possess expertise and the financial strength to evaluate and invest in the capital markets and registered with the Securities Exchange Board of India. There are around 300 QIBs in India.

[10]The 2007 crisis had eroded investor confidence in stock markets.

application size for each anchor investor is INR 100 million. An anchor investor would apply for shares like any regular investor at the price it deems fit. The offer to these investors opens and closes one day before the offer opens to other categories of investors. Allocation to anchor investors are made on a discretionary basis subject to minimum number of two investors for allocation of up to INR.2.5 b and five investors for allocation of more than INR.2.5 b. The number of shares allocated to anchor investors and the price at which the allocation is made are disclosed by the investment bank before the opening of the issue. These investors face a lock-in period of 30 days (on the shares allotted to them) from the date of allotment. The law prohibits entities related to the lead manager or founders of the company from acting as anchor investors. Typical anchor investors are public financial institutions, commercial banks, mutual funds, foreign institutional investors, multilateral and bilateral institutions, venture capital funds, insurance companies, provident funds and pension funds. Several authors have questioned the ability of underwriters to value firms facing valuation uncertainty (Seth et al, 2019; Lowry et al, 2010). The anchor investor program introduces auctions as a mechanism to sell IPOs. Auctions are expected to result in better price discovery.

The Securities Exchange Board of India introduced the call-auction in January 2012 to curb price manipulation and excessive volatility on the listing day[11]. In a call auction market, buyers set the maximum price at which they will buy the shares and sellers set a minimum price at which they will sell the shares. Orders are pooled in the order book but remain unexecuted till the end of the order entry period, when the orders get matched and executed at the single call auction price. At the call, all buy orders are aggregated into a downward sloping demand function and all sell orders are aggregated in an upward sloping supply function. The market opening price and quantity traded are derived based on aggregate supply and demand

[11] The details of trading mechanism are based on documents published by the Bombay Stock Exchange and the National Stock Exchange of India on their respective websites.

for the underlying stock. The orders that trade and the price and quantity at which they trade, are set by multilateral matching, rather than by the sequence of bilateral matching used to determine trades in a continuous market. Reduced price volatility due to multiple matching of orders at a single price, greater liquidity due to deeper demand supply schedule, better price discovery and reduced market impact are some of the purported benefits of call auctions. Because the opening auction is a uniform price action, investors would not have an incentive to improve their bid price in order to acquire priority over others.

In the pre-open session, traders enter their orders for 45 minutes between 9.00 a.m. and 9.45 a.m. Orders entered in this period can be modified or cancelled. The process is randomly stopped for one minute between 9.44 a.m. and 9.45 a.m. The exchange disseminates indicative price, cumulative buy and sell quantities during the order period. Orders are matched, trades are confirmed, and opening price is determined between 9.45 a.m. and 9.55 a.m. Eligible buy limit orders are matched with eligible sell limit orders. Order entry or modification or cancellation is not allowed during this period. There is a buffer period of five minutes during 9.55 a.m. and 10.00 a.m. to ensure that the continuous session starts at the specified time.

Only limit orders (not market orders) are permitted during the special pre-open session. The equilibrium price computation follows the volume maximization principle based on aggregate demand and supply of orders. All orders entered in the system for a particular stock are matched at the same price, i.e., the equilibrium price or the market opening price, if they can be matched. In case more than one price meets the criteria, the equilibrium price will be the price at which there is a minimum order imbalance quantity (unmatched order quantity). The absolute value of the minimum order imbalance quantity is taken into consideration. In case more than one price has the same minimum order imbalance quantity, the equilibrium price will be the price closest to the base price. In case the base price is the mid-value of pair of prices which is closest to it, then the base price itself will be taken as the equilibrium price. The equilibrium price determined in call auction pre-open session is considered the opening price for the day[12]. All unmatched limit orders in the pre-open session are shifted to the order book of the continuous trading session at their limit price on a price-time priority basis, regardless of whether the equilibrium price has been discovered or not. In case the limit price of any unmatched order shifted to the continuous trading session is beyond the applicable price band for that stock, then such outstanding orders are returned.

In case an equilibrium price is not discovered, all orders are cancelled, and the stock continues to trade through a call auction mechanism until the price is determined[13]. Guidelines by SEBI prescribe that the following price bands be applicable for an IPO during the continuous trading session on the listing day: For IPOs with issue size less than ₹2.5 b, the price band in the normal trading session would be ±5% of the equilibrium price otherwise the price band would be ±5% of the offer price. For IPOs with issue size greater than ₹2.5 b, the price band in the normal trading session would be ±20% of the equilibrium price otherwise the price band would be ±5% of the offer price. Further, for IPOs with offer size less than ₹2.5 b stocks can be traded only if one has shares in one's account, i.e., there would not be any speculative trades in these stocks. This period lasts 10 days.

2.2.Data Sources and Sample

To assemble the data set of BSE IPOs between 2006 and 2019 we collect data from the PRIME IPO database, a standard source of IPO data in India (Clarke et al, 2016). Offerings are examined to ensure that data on firm and offer related variables are available for each IPO. The

[12] The clearing price (the price at which trading volume is maximized) is determined and applied to the continuous session. However, the first price in the continuous session bid by an investor could be different from this discovered price.

[13] The Bombay Stock Exchange authorities confirmed to us that there has been no instance where price was not discovered during the pre-opening session.

stock prices for one-month after the listing is obtained from BSE's official website. The data set is then bifurcated into two time periods i.e. before the introduction of pre-opening trading regulation (2006-2011) and after the introduction (2012-2019). As described in Table I, the data set provides a sample of 789 offerings. Of these 338 are from the 2006 – 2011 period and 451 are from the 2012-2019 period[14]. The last column of the table indicates the number of underpriced IPOs in each year. The percentage of underpriced IPOs in the sample is given in the parentheses. Thus 30% of IPOs are overpriced with negative initial returns in the entire sample ranging from 2006-2019.

2.3. Descriptive Statistics and Variable Construction

As stated earlier, the IPO initial return is measured as the percentage difference between the IPO price and the subsequent secondary trading market price. This could be the closing price on the listing day or 21 days, a procedure commonly followed in the U.S to capture the aftermarket price that reflects the true market value (e.g., LOS, 2010)[15]. Prior papers that use Indian data report the listing day initial returns. The price limits on the first ten days may arrest (the volatility of) initial returns. Therefore, we measure initial returns using 21st day prices. Volatility of initial returns are also estimated using 21st day prices. However, in some of our regressions we present the results using Day-1 returns for robustness. Our descriptive statistics show the results using Day-1, Day-11 and Day-21 prices. Figure 1a shows the distribution of initial returns to IPOs over a period of 14 years. The distribution of initial returns to IPO investments is defined as the percent

[14] We began collecting data in October 2019. As a result, our data stops in October 2019.

[15] In U.S. the underwriters resort to price stabilization activities by posting stabilizing bids to influence the prices of freshly issued stocks immediately after the listing. Therefore, prices on the 21st day are assumed to be free of such influences. Price stabilization by underwriters is not popular in India.

difference between the closing price on the 21st day of trading and the offer price. Figure 1a also shows a normal distribution with the same mean and standard deviation as the sample. In addition to a high standard deviation, the initial return distribution is highly positively skewed and leptokurtic (high central peak and heavy tailed). The 789 IPOs between 2006 and 2019 have an average initial return of 14% and a considerably large standard deviation of over 37%. We find that 3% of the IPOs in the sample have a 0% initial return after the introduction of pre-opening trading regulation (2012-2019) whereas no IPO had a 0% return during the pre-regulation period (2006-2011). This is consistent with the results of Ruud (1993) and Hanley et al, (1993) that price stabilization activities influence the trading prices of IPO stocks in the days immediately following the offering. In our context, the trading controls provide stabilization to IPO stocks. In Figure 1b we show the distribution of initial returns defined as the percent difference between the closing price on the 1st day of trading and the offer price. Again, the distribution exhibits skewness (=2.74) and kurtosis (=15.38). In Figure 2a we plot the monthly mean and standard deviation of listing day initial returns to IPO and the number of IPOs by year from 2006 to 2019. Initial returns to IPO investments are defined as the percent difference between the closing price on the listing day and the offer price. The graph shows that the mean and volatility of initial returns follow cycles and closely track each other. A closer scrutiny suggests that, in 2011, the volatility was extremely high. We see that volatility and the absolute level of underpricing have considerably reduced following the introduction of pre-opening trading and price controls. In Figure 2b we plot the variance of 11- and 21-day initial returns to IPOs during 2006 to 2019. Initial returns to IPO investments are defined as the percent difference between the closing price on the 11th or 21st trading day respectively and the offer price. Again, we see that volatility has declined substantially after 2012. This graphical analysis provides early evidence to support our hypothesis that the new mechanism can potentially arrest the volatility of IPO returns.

The excessive volatility can potentially drive investors away from IPOs. One of the benefits of curbing volatility is that more firms can go public. That is, investors would be more willing to invest in IPO firms. This notion is supported by Figure 3, which shows that the number of IPOs has steadily climbed since 2012. This figure also supports the notion that IPOs come in waves. Pastor and Veronesi (2005) argue that market-wide uncertainty influences the decision of firms to go public. By extension, this uncertainty compounds the investors' and underwriters' inability to value IPOs thereby leading to excessive volatility. Figures 2a and 3 show that a drop-in IPO activity is preceded by high aggregate volatility of IPO initial returns.

2.4. Variable Construction

In our regressions we control for firm size, offer size, industry risk, lead manager reputation, VC backing, and investor demand (subscription). Earlier papers by Beatty and Ritter (1986); Megginson and Weiss (1991) show that IPOs backed by reputed underwriters and venture capitalists are less underpriced. Similarly, younger, and smaller firms may suffer from asymmetric information because of which they may be more underpriced (Rock, 1986). Table II presents the description of variables and the sources of data. We discuss some of the variables here:

***Underwriter reputation*:** Equals one if the IPO is underwritten by top 10 underwriters in terms of market share at the time of the IPO and zero otherwise

***Tech dummy*:** Equals one if the firm is in a high-tech industry (biotech, computer equipment, electronics, communications, and general technology), and zero otherwise.

***Venture capital dummy*:** Equals one if the firm received financing from venture capitalists prior to the IPO, and zero otherwise

Log (Shares): The natural logarithm of the shares issued in an IPO

Log (Firm Age + 1): The natural logarithm of the number of years since the firm was founded (at the time of the IPO) plus one.

Log (Total Assets): The natural log of total assets, a proxy for firm size.

Log (Subscription): The natural log of total subscription by all investors, in times. The National Stock Exchange and Bombay Stock Exchange have nationwide trading networks and conduct online IPOs. The process allows investors to observe bids made by different classes of investors. This makes the book-building process transparent. Consequently, investor demand can be observed when the book building takes place[16]. In India shares are offered to three categories of investors: qualified institutional buyers (QIB), retail investors and non-institutional investors (e.g., high net worth individuals). Subscription can be observed for these investor categories.

Panels A through C of Table III contain the descriptive statistics of mean and volatility of initial returns for the entire sample period. We calculate the average and standard deviation of initial return in each month for all IPOs conducted in that month. Initial return itself is calculated as the percent difference between the listing day or 11th day or 21st day price and the offer price. Panel A shows that the average listing day underpricing during 2006-2019 was 14.09%. A median IPO generated 7.33% listing day returns. The listing day returns are highly variable with a standard deviation of 27.07%. The extent of underpricing is even more if we were to measure it with 11th day or 21st day prices. Their variability is also much higher. In Panels B and C, we present the summary statistics for 2006-2011 and 2012-2019. The average listing day initial return during 2006-2011 was 21.99% but only 8.43% during 2012-2019. A median IPO generated 20.04% initial returns during 2006-2011 but only 5.11% during 2012-2019. The volatility of listing day underpricing has declined by 50%. Similarly, the volatility of 11-day returns has reduced from 32.44% to 26.50% and that of 21-day returns from 33.19% and 31.9%. One reason for the drop in initial returns and their volatility is that the total subscription (i.e., investor demand for an IPO)

[16] Therefore, we do not need to take Price Update as proxy for investor demand as in the U.S. context.

has fallen from 1.668x to 0.8x. This supports the notion that excessive demand for IPOs either because of unmet demand or speculation by investors drives IPO initial returns and their volatility. The other reason is that the former period (2006-2011) contains the global financial crisis years, and this might have driven up volatility. We explore these explanations in Table IV.

In Panel D of Table III, we present the monthly average and standard deviation of initial returns for all IPOs. Columns 2, 3 and 4 show the mean, median and standard deviation of these two statistics during 2006-2011, 2012-2019 and 2006-2019. Column 5 shows the correlation between the two. We find that the cross-sectional standard deviation is much higher than the average initial return and they are highly correlated (0.69 for the entire period and 0.88 during 2012-2019). The correlation is much less if we exclude the IPOs issued during the global financial crisis. The next 6 columns show the auto correlations of our metrics for up to six-lags. We find that the autocorrelations of average returns are similar to those of volatility of underpricing. Overall, our results suggest that the distribution of returns changes through time and often the initial return and volatility are correlated.

Panel A of Table IV shows the correlation between the variables used in our analyses. The monthly volatility of underpricing computed with 11th day prices is significantly correlated with underpricing measured with respect to the listing day prices and the 11th day IPO prices. Likewise, the volatility of underpricing computed with 21st day prices is significantly correlated with underpricing measured with respect to the listing day, 11th day and 21st day prices. This supports the argument by LOS that mean, and volatility are related. We also find that the post-regulation dummy is significantly negatively correlated with the volatility of underpricing. The crisis years are associated with significantly higher underpricing and volatility. IPOs that are more highly subscribed by investors and tech firms are associated with higher underpricing and volatility.

Panel B of Table IV shows correlations between the monthly averages and standard deviations of IPO initial returns and monthly, average IPO characteristics. The sample consists of IPOs between 2006 and 2019 and for the two sub periods 2006-2011 and 2012-2019. Earlier research suggests that firms that are subject to greater asymmetric information are more likely to be underpriced and they may also be more volatile. We measure the average initial return and standard deviation of underpricing in each month and examine the correlation between these metrics and average values of firm characteristics such as firm size on a monthly basis. Our hypothesis is that the months in which a greater proportion of firms with information asymmetry go public may be associated with higher underpricing and volatility. But we expect the trading regulation to reduce the extent of correlation after 2012. In columns 1 and 2 we present the correlation with average underpricing (measured with respect to the 21st day price) with and without the global financial crisis years. The third column presents the correlation with average underpricing after 2012. The table shows that the average underpricing in months in which more tech firms or smaller firms go public are no longer associated with high underpricing. When more venture capital backed firms go public, the underpricing is significantly lower although the correlation was positive before 2012. The correlation values in column 3 are mostly insignificant and negative. Columns 1 and 2 show that when the subscriptions by retail and institutional investors are high, the underpricing is high. But the correlation becomes negative and insignificant after 2012 (column 3). In the next three columns we present the correlation between the average standard deviation of underpricing and average firm characteristics. The table suggests that volatility is not significantly correlated with our proxies for firm risk (column 6).

3. Empirical Results

In the previous section we presented univariate results to support our hypothesis that the new legislation has likely reduced initial return and its volatility. In this section we present the results of our regression analysis. The discussion is divided into five sub-sections.

3.1. Ordinary Least Squares Regression

As a baseline analysis we model the level of initial returns using an ordinary least squares regression framework. We estimate the following equation:

$$IR_i = \beta_0 + \beta_1 \text{ (Post-Regulation Dummy)} + \beta_2 \text{ (Underwriter Reputation Dummy)} + \beta_3 \text{ Log (Shares)} + \beta_4 \text{ (Technology Dummy)} + \beta_5 \text{ (VC Dummy)} + \beta_6 \text{ Log (Firm Age + 1)} + \beta_7 \text{ Log (Total Assets)} + \beta_8 \text{ (Global Financial Crisis Dummy)} + \beta_9 \text{ Log (Total Subscription Times)} + \varepsilon_i \qquad \textbf{(1)}$$

In the next step we present the results of Maximum Likelihood Estimation whose results will be compared with the OLS benchmark.

Table V presents the results of our OLS regression. The dependent variable in our regressions is the initial return of IPOs. In regression 1 we use a crisis indicator variable set equal to 1 if an IPO was made during 2007 and 2008. The variable of interest is the post regulation dummy set equal to 1 if an IPO was made after 2012. The coefficient of post regulation dummy is negative and significant at the 5% level, which suggests that IPOs are much less underpriced after the introduction of trading controls. The coefficient of crisis dummy is significantly positive suggesting that the IPOs made during 2007 and 2008 were highly underpriced. In regression 2 we exclude the IPOs conducted during the crisis years and introduce subscription by investors in various categories. Again, we find a substantial reduction in underpricing after 2012. The coefficient of firm size (total assets) is significantly negative, which indicates that smaller firms are more highly underpriced. IPOs underwritten by reputed underwriters are also more highly underpriced. While the certification hypothesis would suggest that IPOs underwritten by reputed lead managers should be less underpriced, we find the opposite. It is likely that investors take the association with reputed investment banks as proxy for IPO quality and bid in large numbers. This may lead to unmet demand in the pre-market and higher underpricing in the aftermarket.

3.2.Maximum Likelihood Estimation

Table VI shows the results of maximum likelihood estimation in which we model both the level and volatility of initial returns as a function of offer and firm characteristics. We estimate the following equations:

$$IR_i = \beta_0 + \beta_1 \text{ (Post-Regulation Dummy)} + \beta_2 \text{ (Underwriter Reputation Dummy)} + \beta_3 \text{ Log (Shares)} + \beta_4 \text{ (Technology Dummy)} + \beta_5 \text{ (VC Dummy)} + \beta_6 \text{ Log (Firm Age + 1)} + \beta_7 \text{ Log (Total Assets)} + \beta_8 \text{ (Global Financial Crisis Dummy)} + \beta_9 \text{ Log (Total Subscription Times)} + \varepsilon_i \quad \textbf{(2)}$$

$$\text{Log (Var (IR))} = \gamma_0 + \gamma_1 \text{ (Post-Regulation Dummy)} + \gamma_2 \text{ (Underwriter Reputation Dummy)} + \gamma_3 \text{ Log (Shares)} + \gamma_4 \text{ (Technology Dummy)} + \gamma_5 \text{ (VC Dummy)} + \gamma_6 \text{ Log (Firm Age + 1)} + \gamma_7 \text{ Log (Total Assets)} + \gamma_8 \text{ (Global Financial Crisis Dummy)} + \gamma_9 \text{ Log (Total Subscription Times)} + \varepsilon_i \quad \textbf{(3)}$$

The variance of the error from the regression model in (2) is assumed to be related to the same firm and offer characteristics that affect the level of initial returns. We estimate three models of the level and volatility of initial returns. The dependent variable in model 1 is the average initial return. We exclude the IPOs made during the global financial crisis years as they may contaminate the results. The variable of interest is the post regulation dummy. Our regression analysis (column 1) shows that there is a significant decline in the level of initial returns after the enactment of the legislation. This result is similar in magnitude to the OLS results we presented in Table 5. The coefficients of other variables are qualitatively similar to the OLS regressions.

In the next two regressions we model volatility of initial returns. In the volatility regression (column 2) we include IPOs during the global financial crisis years i.e., 2007 and 2008. In the next volatility regression (column 3) we exclude them. Again, the coefficient of post regulation dummy is significantly negative in columns 2 and 3, which suggests that the volatility declined significantly after the introduction of the regulation by 3.9 % and 4.27% respectively. Columns 2 and 3 show that smaller firms are more volatile. This is consistent with prior literature. Strangely, investor demand (in retail, institutional and non-institutional categories) is unrelated to both the level and volatility of initial returns. We would expect investor demand in the pre-market to drive up initial return in the after-market. Overall, our results indicate that the volatility reduces after controlling for the variation in the types of firms going public over time.

3.3. Asymmetric Information and the Volatility of Initial Returns

Price limits during the first ten days of trading of an IPO is a form of insurance provided to uninformed investors to reduce the winner's curse. Price support should be particularly useful in situations in which information asymmetries among different market participants are severe. Based on this reasoning, a natural empirical prediction is that stocks with greater asymmetric information should benefit more from the price limits imposed on them. Information asymmetries arise when some market participants have better information about the stock's value than other investors. A common assumption is that larger uncertainty and more information asymmetries are associated with smaller, younger firms (Ritter, 1984), and IPOs facing valuation uncertainty. We use anchor backing and the firm's age as proxy for asymmetric information. Firms that face valuation uncertainty either because of their size or age cannot credibly convey their quality because of which they may find an association with anchor investors attractive. To the extent that there is greater information asymmetry about young firms, we expect the initial returns of these firms to be higher and the pricing to be less precise their expected initial return would be higher and the dispersion of expected initial returns greater, ceteris paribus, than an older firm (Lewellen, 2006). Likewise, smaller firms suffer from asymmetric information (Rock, 1986). We examine underpricing, volatility, and changes in volatility for anchor backed IPOs and young firms to determine whether the new regulation reduced the pricing errors of these firms.

3.3.1. Anchor Backed IPOs

In this sub section we examine whether anchor backed IPOs experience lower initial returns and volatility of initial returns after the introduction of price limits. As an alternative to the regression approach, we use PSM and DID estimation to establish causality.

3.3.1.1.Propensity Score Matching of Initial Returns

We consider anchor backing as the treatment, anchor-backed IPOs as treated units, and non-anchor-backed IPOs as untreated units. The outcome is the observed initial return or its volatility. The propensity score is estimated during 2009–2011 (the period elapsed between the introduction of anchor investor legislation and the introduction of the pre-opening trading) and 2012-2019 (Post AI and pre-opening trading legislations) respectively, using controls such as the number of shares offered, firm age, firm size, technology dummy, subscription by institutional and retail investors in a logit regression analysis. We employ a two-stage procedure to match scores. In the first stage, the probability of attracting anchor investors is estimated by a logistic regression in which the dependent variable is an Anchor Dummy, a binary variable, and the covariates are the observed characteristics of the vector. In the second stage, the predicted probabilities from the first stage are used as propensity scores to match observations from the two groups. That is, anchor-backed IPOs are matched with non-anchor-backed IPOs.[17] We employ nearest neighbour 1:2 matching with replacement. In the first step, we consider IPOs made during 2009–2011 because the pre-opening trading rules and price limits were introduced in January 2012. The absolute percentage difference

[17]We also verify that covariates are balanced across treatment and comparison groups.

between the issue sizes had to be less than 0.3 to be a successful match. In the second step we replicate this for 2012-2019.

The average differences in initial return and its volatility between anchor-backed and non-anchor-backed IPOs and the *t*-statistics are summarized in Table VII. Table VII shows that anchor backed IPOs were more highly underpriced than non-anchor IPOs before 2012. The average underpricing difference is 25.63%, which is significant at the 5% level. The same table also reports the difference in underpricing after 2012. Underpricing falls dramatically and anchor backed IPOs are much less underpriced than non-anchor IPOs. The difference between the two is 34.29%. This result supports the hypothesis that anchor backed IPOs that face asymmetric information and valuation uncertainty were greatly benefited after 2012 by lowering pricing errors.

3.3.1.2.Difference-in-Difference Estimation of Initial Returns and Volatility

In the next step, we perform a DID estimation in which anchor backing is our treatment. Anchor-backed IPOs denote the treated sample and non-anchor IPOs denote the untreated sample. We estimate the following regression equation:

$$UP = b_0 + b_1\,(Post\ Regulation\ Dummy) + b_2\,(Anchor\ Dummy) + b_3\,(DID) + b_i\,(X_j) + \varepsilon_i \qquad \textbf{(4)}$$

where UP is the average initial return. We measure initial returns using both listing day's closing prices (column 1) and 21st day closing prices (column 2). The parameters are post regulation dummy, which is a dummy variable for IPOs launched after 2012, Anchor Dummy and DID, which is the product of post regulation dummy and Anchor Dummy. X_j are covariates uses in our UP regressions. Table VIII shows the results of our DID estimation. The DID coefficient in model 1 (−14.34) and model 2 (-35.92) are significant at the 10% level.

In addition to initial returns, we perform a difference-in-difference estimation of volatility of initial returns. We estimate the following equation:

$$Log\ (Var(UP)) = b_0 + b_1\,(Post\ Regulation\ Dummy) + b_2\,(Anchor\ Dummy) + b_3\,(DID) + b_i\,(X_j) + \varepsilon_i \qquad \textbf{(5)}$$

Table IX presents the results of our DID estimation. After controlling for firm characteristics, we find a significant decline in the volatility of initial returns after 2012 for anchor backed IPOs relative to non-anchor IPOs. This supports our hypothesis that the regulation benefits riskier firms by reducing the extent of underpricing as well as its variability. As an alternative to the DID estimation we run a OLS regression in which the variable of interest is the product of post regulation dummy and anchor backed dummy. The results are displayed in Table X. Again, we document a significant reduction in volatility.

3.3.2. *Young Firms*

The other proxy we use for asymmetric information is firm age. Younger firms cannot credibly convey their quality because they lack a long history of successful operation. Such firms may also find price limits useful. We run an ordinary least squares regression with the volatility of initial returns as the dependent variable. The variable of interest is the product of post regulation dummy and young firm dummy. We model the volatility of 21-day and listing day initial returns as a function of the product of post regulation dummy and a young firm dummy, and covariates that we use in prior regressions of volatility. Firms are categorized as young or old based on the number of years of existence since inception at the time of the IPO. All firms falling in the bottom quartile in the entire dataset are classified as young and assigned a dummy variable equal to 1. The remaining firms are classified as old and assigned 0. We estimate the following equation:

$$Log\ (Var\ (IR_t)) = \beta_0 + \beta_1\ (Post\ Regulation\ Dummy) + \beta_2\ (Young\ Firm\ Dummy) + \beta_3\ (Post\ Regulation\ Dummy * Young\ Firm\ Dummy) + \beta i\ (Xi_t) + \varepsilon_i \quad \textbf{(6)}$$

Table XI presents the results of our OLS regression. In column 1 the dependent variable is the natural log of variance of residuals of 21-day underpricing extracted from the OLS regression as in Table V. The coefficient of post regulation dummy * young firm dummy is significantly negative suggesting that the volatility of 21-day returns fell by 4.34% for younger firms after 2012.

In column 2, for robustness check, we repeat the analysis by estimating the natural log of variance of listing day returns. Again, the coefficient of post regulation dummy * young firm dummy is significantly negative (2.39%). These results suggest that the trading regulations introduced in the after-market led to a decline in volatility of initial returns of IPOs made by younger firms as well.

In the next stage we examine the change in volatility of younger firms for 5 years surrounding the introduction of the law. In a DID design, there is a single point in time during which the treatment group is subject to the new treatment whereas the control group does not receive the treatment. The IPOs in our sample did not occur at the same point in time. Therefore, we cannot perform a true DID estimation while matching young and old firms. We resort to a regression that simulates the DID estimation. We match firms drawn from the sample two years after the introduction of the legal reform (2014) with firms drawn from the sample two years before the regulation (2010) on the basis of firm age. We model the change in volatility of 21-day initial returns as a function of post regulation dummy, a small firm dummy, the product of the two and covariates that we use in prior regressions of volatility. Firms are categorized as young or old based on the number of years of existence since inception at the time of the IPO. All firms falling in the bottom quartile in the entire dataset are classified as young and assigned a dummy variable equal to 1. The remaining firms are classified as old and assigned 0. Thus, IPOs made by young firms become our treated group. We exclude the IPOs during the global financial crisis as they may contaminate our results. The parameters are Post Regulation Dummy, which is a dummy variable for IPOs launched after 2012; Young Firms Dummy and the product of Post Regulation Dummy and Young Firms Dummy. Xi are covariates. The absolute values of control variables are measured at the end of financial year 2012 (i.e., March 31, 2012) for firms in the same age category.

We estimate the following equation:

$$\triangle\ Log\ (Var\ (IR_t)) = \beta_0 + \beta_1\ (Post\ Regulation\ Dummy) + \beta_2\ (Young\ Firm\ Dummy) + \beta_3\ DID + \beta i\ (Xj_t) + \beta j\ (\triangle Xjt) \qquad \textbf{(7)}$$

Our methodology is similar to Lin and Flannery (2013) except that it is not a DID estimation. In our models we incorporate the changes in covariates from two years before 2012 (i.e., 2010) to two years after (i.e., 2014) the implementation of the regulation. The relative changes between lag and forward values of covariates are measured as $Xi_t = (Xi_{t+2} - Xi_{t-2})/Xi_{t-2}$. Since we are also interested in the change in variance of initial returns due to a change in covariates (Xj), we assume that at time t+2, Xj changes to $Xj_{t+2.}$ In model 1 we use only the changes in the covariates and in model 2 we use both absolute values and changes in the covariates. Table XII shows the results of our estimation. Our analysis suggests a significant decline in volatility in both the models. The coefficients of the product in model 1 (i.e., -1.946) and model 2 (i.e., -2.109) are significant at the 10% level.

3.4. Market Conditions and the Volatility of IPO Initial returns

In their survey of the IPO literature, Ritter and Welch (2002) conclude that market conditions are the most important factor in the decision to go public. Pastor and Veronesi (2005) argue that market-wide uncertainty influences the decision of firms to go public. By extension, this uncertainty compounds the inability of investors' and underwriters' to value IPOs thereby leading to volatility in IPO initial returns. Therefore, apart from firm characteristics, market volatility may explain the variability in IPO initial returns (LOS). We examine whether the volatility of IPO initial returns reduces after controlling for measures of market-wide volatility since the introduction of regulatory price limits. We consider three proxies for market-wide uncertainty: 1) implied volatility of index options reflected in the volatility Index (i.e., India VIX) 2) Volatility of the stock market index (Bombay Stock Exchange Sensitive Index, Sensex) and 3) S&P BSE IPO Index.

We take the volatility index (VIX) of the National Stock Exchange as one of the proxies for market-wide uncertainty. India VIX indicates the investor's perception of the market's volatility in the near term. That is, it shows the expected market volatility over the next 30 calendar days. The higher the values of India VIX, higher is the expected volatility and vice-versa. India VIX is computed by the National Stock Exchange based on the order book of NSE 50 Index (NIFTY) Options. The index was started on March 2, 2009. The best bid-ask quotes of near and next-month NIFTY options contracts traded on the Futures and Options segment of NSE are used for computation of India VIX. India VIX uses the computation methodology of CBOE.

The S&P Bombay Stock Exchange 30 Index (Sensex) is the oldest index in the country. It is a market weighted index of 30 well established companies on the Bombay Stock Exchange. They are the largest and most actively traded companies that represent the various industrial sectors of the Indian economy.

The Bombay Stock Exchange launched the S&P BSE IPO index on August 24, 2009, to measure the performance of firms after successful completion of their initial public offering (IPO). It is a barometer of primary market conditions in the Indian capital market. A company must have a minimum float-adjusted market capitalization of INR 1 billion on the first day of listing. A company is included in the index on the third day of listing subject to the fulfilment of the minimum float-adjusted market capitalization criteria. A company is excluded from the index at the open of the Monday following the third Friday of the month after the completion of one year of listing. The IPO index has a ceiling for weights of index constituents. Market capitalization weights of index constituents are limited to 20%. Weights are updated at each monthly rebalancing. The index contains a minimum of 10 stocks of IPO firms at any point in time.

Volatility of BSE IPO Index returns provide us a mechanism to gauge the volatility of recent IPOs. When the index volatility is high, we expect the market-wide uncertainty for IPOs to be high.

In Figure 4 we plot volatility of 21-day IPO initial returns, VIX (expected volatility of Sensex) and the actual, realized, volatility of the Sensex. We see that the volatility of IPO initial returns has declined substantially, especially after 2015. IPO initial return volatility seems to mirror the expected volatility of the market. In Figure 5 we plot the volatility of IPO Index returns, VIX and the actual, realized volatility of the Sensex. Since the IPO index measures returns of IPOs for 1 year, essentially it measures longer term returns to IPOs. The graph shows that the IPO index returns closely track the market.

Monthly initial returns have both time-series and cross-sectional dimensions. The IPOs are done by different firms at different point of time in a month, implying a cross-sectional component and a time-series component, respectively. Therefore, in order to control for market-wide volatility, LOS construct two measures computed in both the time series and cross section. Time series volatility is estimated as the monthly standard deviations daily returns using the BSE Sensex. The cross-sectional volatility is measured as the standard deviation of firm-specific monthly cumulative returns for the 30 firms included in the Sensex. Time series volatility measures the aggregate index movement within a month whereas the cross-sectional volatility measures the firm specific volatility. Time series volatility is due to market-wide information while cross sectional volatility is due to firm specific information (Bessembinder et al, 1996). Inflow of market-wide, systematic, information contributes to time series volatility and inflow of firm specific information contributes to cross sectional volatility.

Table XIII reports the results of our maximum likelihood estimation. The procedure is similar to Table VI except that we control for the two-volatility metrics. For each IPO, both the cross-sectional dispersion and the time-series volatility are calculated over the 21 trading days prior to the offer date. The variable s^2_{t-1} is the time-series variance of the Sensex returns for the 21-trading days ending at day $t - 1$. The variable c^2_{t-1} is the cross-sectional variance of the 21-trading-day returns to each stock on Sensex ending at day $t - 1$.

The dependent variable is the volatility of initial returns of IPOs. The variable of interest is the post regulation dummy. We model both the absolute level and the volatility of initial returns in columns 1, 2, and 3. In column 2 and 3 we measure volatility using both listing day as well as 21-day returns. We document a reduction in both initial returns and volatility of initial returns after controlling for market-wide volatility. There is a positive relation between cross sectional volatility and volatility of initial returns of IPOs. However, time series market volatility has an insignificant impact on the level of initial returns. Overall, it appears that firm characteristics have a more significant impact on the variability of initial returns than market-wide factors.

In the next step we examine whether firms facing asymmetric information and valuation uncertainty too experience in a decline in the level and volatility of initial returns after adjusting for market volatility. We perform a difference-in-difference estimation. The regression equation is:

$$IR = b_0 + b_1\,(Post\ Regulation\ Dummy) + b_2\,(Anchor\ Dummy) + b_3\,(DID) + b_i\,(X_j) \qquad \textbf{(8)}$$

The dependent variable in column 1 is the initial return measured using listing day closing price and that in column 2 is initial return measured using 21st day closing price. The parameters are post regulation Dummy, which is a dummy variable for IPOs launched after 2012; Anchor Dummy and DID, which is the product of post regulation Dummy and Anchor Dummy; and X_i are covariates. The variable of interest is the DID. The regressions include the effect of monthly cross sectional (CS) volatility of BSE Sensex[18]. Table XIV reports the results. We find that anchor

[18] The time series volatility has poor explanatory power. Consequently, we dropped it.

backed IPOs experience lower underpricing after controlling for market volatility. In Table XV we replicate the analysis with log of variance of initial returns as the dependent variable.

We estimate the following equation:

$$Log\ (Var\ (UP_t)) = b_0 + b_1\ (Post\ Regulation\ Dummy) + b_2\ (Anchor\ Dummy) + b_3\ (DID) + b_i\ (X_j) + \varepsilon_i \quad \textbf{(9)}$$

The coefficient of DID indicates that volatility increases by a marginal 1.09%. The coefficients of time series and cross-sectional market volatility are insignificant, which suggests that market volatility has no bearing on the volatility of underpricing.

3.5. Stock Return Volatility

While price limits reduce the volatility of 21-day initial returns, it is not clear whether they reduce the long-term stock return volatility in the after-market. It is quite possible that there could be volatility spillover over a longer time window. The after-market volatility is a proxy for ex ante IPO uncertainty (Habib and Ljungqvist, 2001; Aggarwal et al, 2002; Ritter, 1984 b). Since the pre-opening trading auction can potentially result in better price discovery and the price limits can truncate extreme stock price movements, it is likely that stock return volatility may be lower especially for riskier firms. Prior research shows that anchor backed IPOs have lower stock return volatility (Bhattacharya et al, 2020). We test whether this is particularly true after 2012. We estimate the following model:

$$S.D = \alpha + \beta_1\ (Post\ Regulation\ Dummy) + \beta_2\ (Anchor\ Dummy) + \beta_3\ (DID) + \beta_i\ (X_j) + \varepsilon_i \quad \textbf{(10)}$$

We control for firm size (total assets), IPO proceeds, firm age, group affiliation, underwriter rank, volatility of the index, Tech dummy, venture capital backing, crisis dummy, subscription by institutional, non-institutional and retail investors.

The lower the information asymmetry about a firm, the lower is the risk and volatility of returns. Ritter (1984) suggests a negative relation between firm age and uncertainty about the firm's value. Barry and Brown (1984) find a positive relation between firm-specific information and firm size. We therefore expect firm size and age to be negatively associated with aftermarket volatility. Similar argument can be made for IPO size. Small IPOs may be speculative that results in higher volatility of after-market returns. We expect IPOs with a venture capital backing and those underwritten by reputed underwriters to have lower volatility. Tech firms, in general, are more volatile because of their inherent business risk. Volatility of returns from IPOs may mirror market-wide volatility. We estimate market-wide volatility using the standard deviation of daily returns of the S&P BSE Sensex over matching intervals and include it as an explanatory variable to control for market risk. Finally, excessive investor demand creates temporary imbalances that may contribute to volatility of IPO returns. Therefore, we control for subscription in different investor categories. We report the results of our regression in Table XVI. The dependent variable is the standard deviations of daily stock returns over the first 130 days after the listing. The coefficient of DID shows that the volatility of daily stock returns has declined by 37.5% after 2012. The volatility of stock returns is insignificantly related to market volatility. Contrary to what we would expect, Tech firms have lower volatility. IPOs that are highly subscribed by high net-worth individuals have higher volatility.

4. Conclusion

Regulators are concerned about not just the level but also the volatility of IPO initial returns. In this article we document the monthly volatility of initial returns, which varies considerably through time and is related to the average underpricing. We examine a natural experiment that imposes regulatory price limits and a pre-opening trading session for freshly listed IPOs, which could potentially reduce both the level and variability of initial returns. We document significant reductions in both. Since price limits could benefit riskier firms more, we study anchor backed IPOs and young firms that face asymmetric information and valuation uncertainty. We find that the experiment has been successful in reducing their initial returns and variability. This result holds when we control for market-wide volatility. Further, the experiment has also been successful in bringing down the long-term stock return volatility of these IPOs up to 130 days after listing. We conclude that although price limits are not useful in curbing the volatility of listed, seasoned, firms, they can be useful in the context of IPOs.

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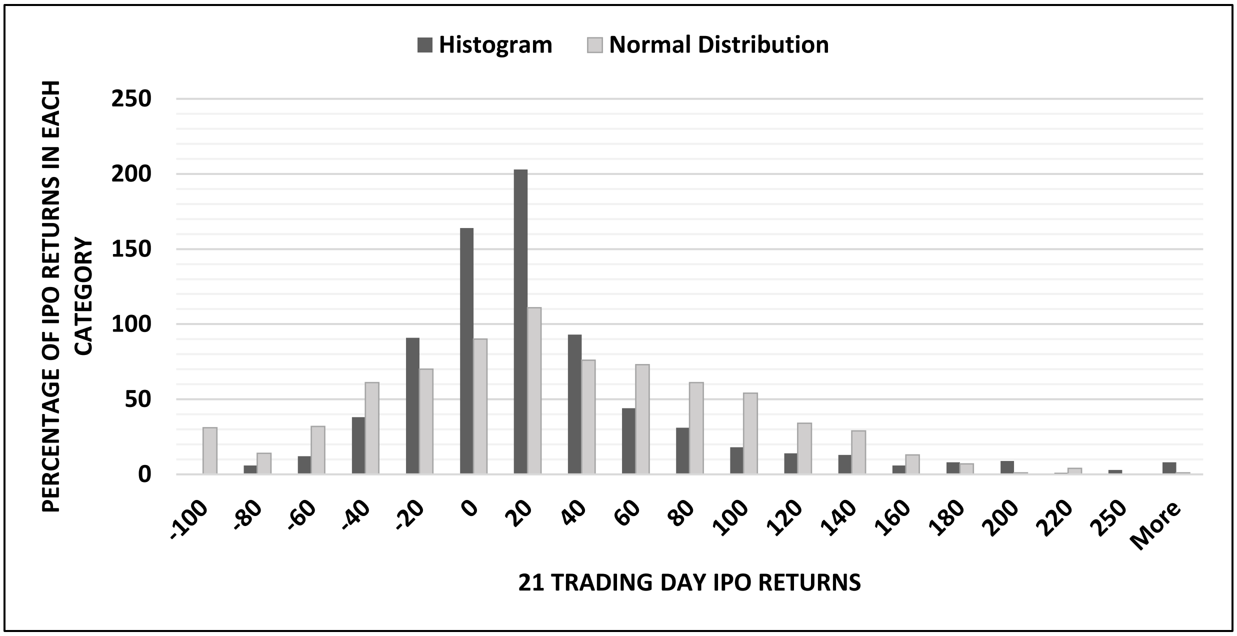

Figure 1a. Frequency distribution of first month IPO returns, 2006-2019. Distribution of initial returns to IPO investments is defined as the percent difference between the closing price on the 21st day of trading and the offer price. In addition to having a high standard deviation, the initial return distribution is highly positively skewed (>+1) and leptokurtic (>3, high central peak and heavy tailed).

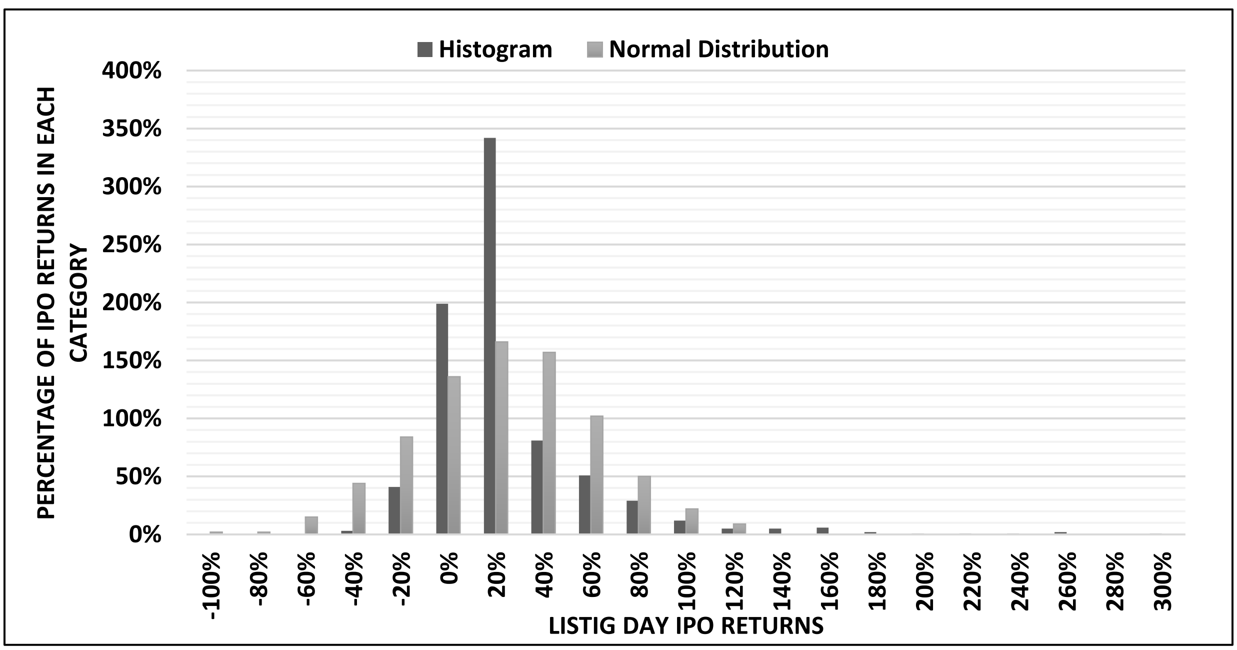

Figure 1b. Frequency distribution of listing day IPO returns, 2006-2019. Distribution of initial returns to IPO investments, defined as the percent difference between the closing price on the 1st day of trading and the offer price.

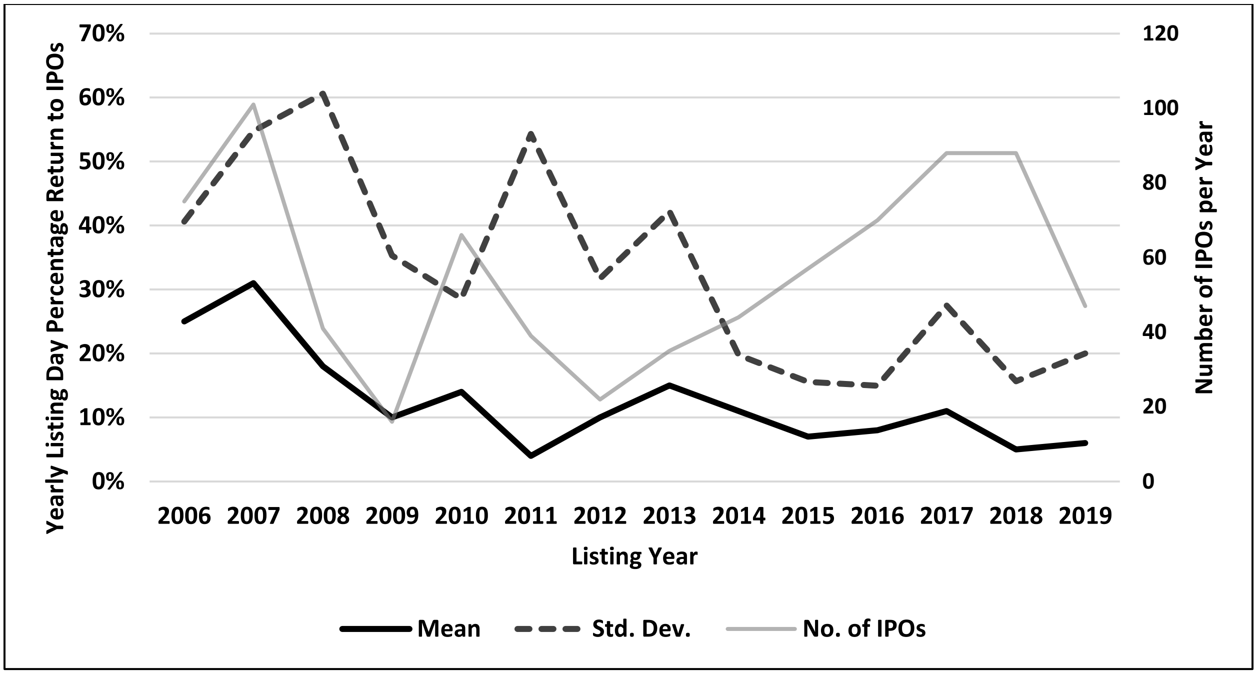

Figure 2a. Mean and Standard Deviation of listing day initial returns to IPO and the number of IPOs by year, 2006-2019. Initial returns to IPO investments are defined as the percent difference between the closing price on the listing day and the offer price. Each year initial returns to IPOs during that year are calculated. The solid black line represents the mean underpricing during the year and the dotted line represents the standard deviation (volatility) of these initial returns. The thin grey line represents the number of IPOs per year.

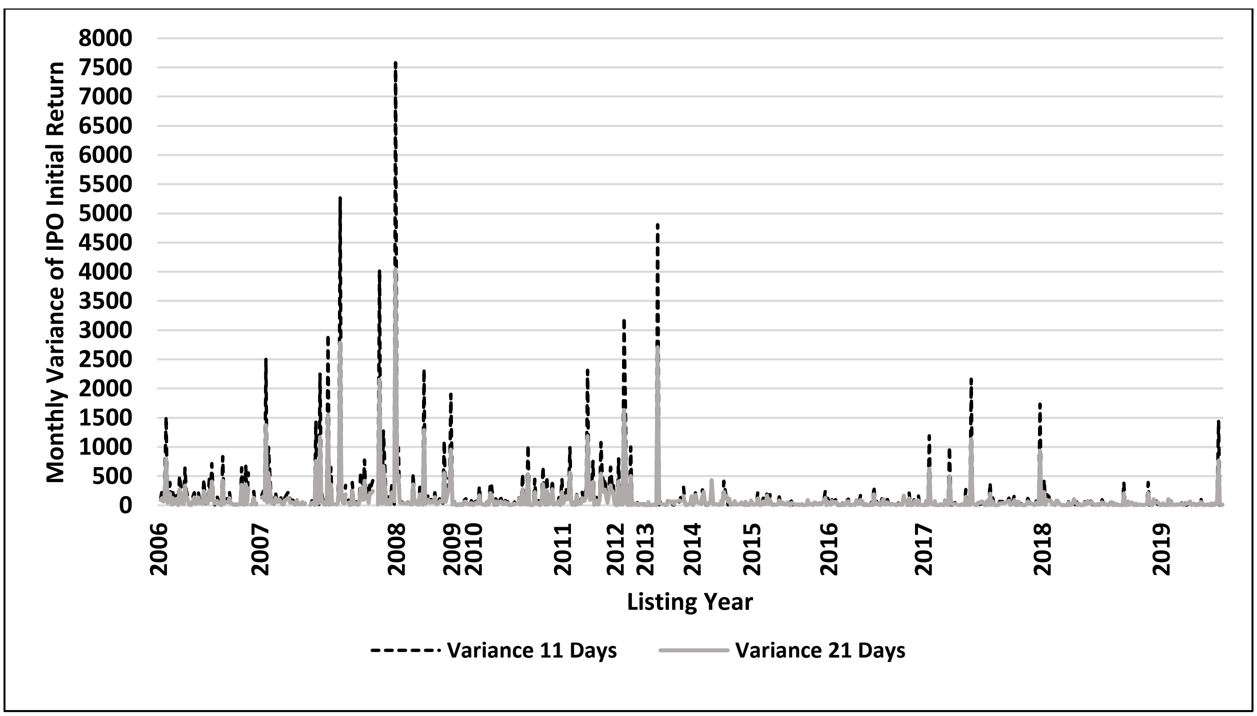

Figure 2b. Variance of 11- and 21-days initial returns to IPO by year, 2006-2019. Initial returns to IPO investments are defined as the percent difference between the closing price on the 11th and 21st trading day respectively, and the offer price. Each month initial returns to IPOs for 11 and 21 trading days during that month are calculated, respectively. The dotted black line depicts the variance (volatility) of 11day initial returns and the solid grey line depicts the variance (volatility) of 21day initial returns.

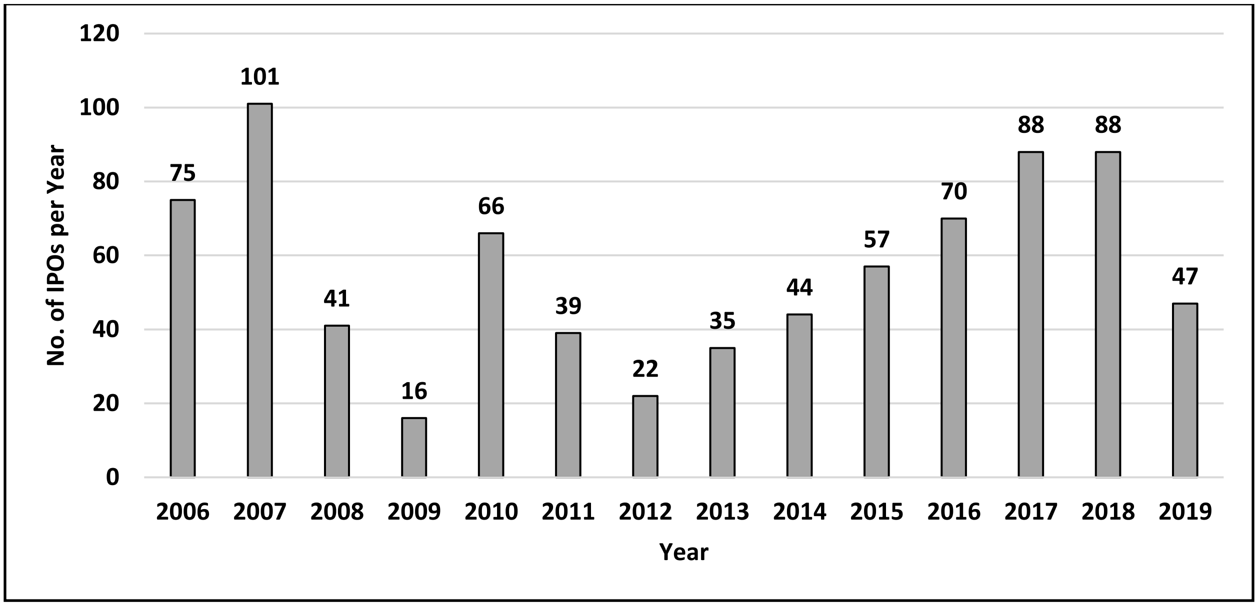

Figure 3. Number of IPOs, 2006-2019. Each bar shows the total number of IPOs on Bombay Stock Exchange from 2006 to 2019.

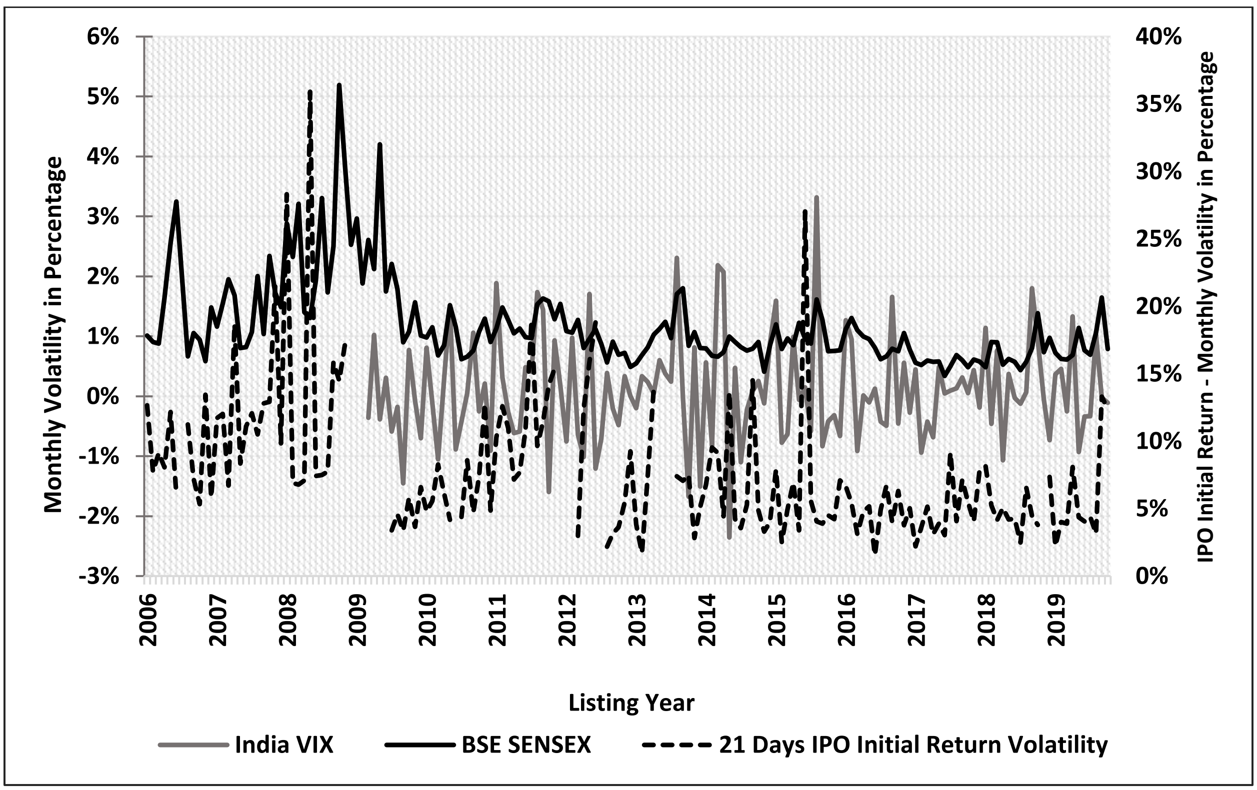

Figure 4. Volatility of Initial Returns to IPOs, India VIX and Volatility of S&P BSE SENSEX, 2006-2019. Volatility of SENSEX returns, and IPO Initial Returns are calculated for each month. Similarly, the average monthly volatility using India VIX is calculated. The monthly volatility of 21 days IPO initial returns (dotted line) is shown on the secondary vertical axis on a higher scale as compared to primary vertical axis. The breaks in the volatility chart indicate absence of IPOs during that period. The solid lines represent the monthly volatility of BSE SENSEX and average monthly volatility of India VIX, respectively.

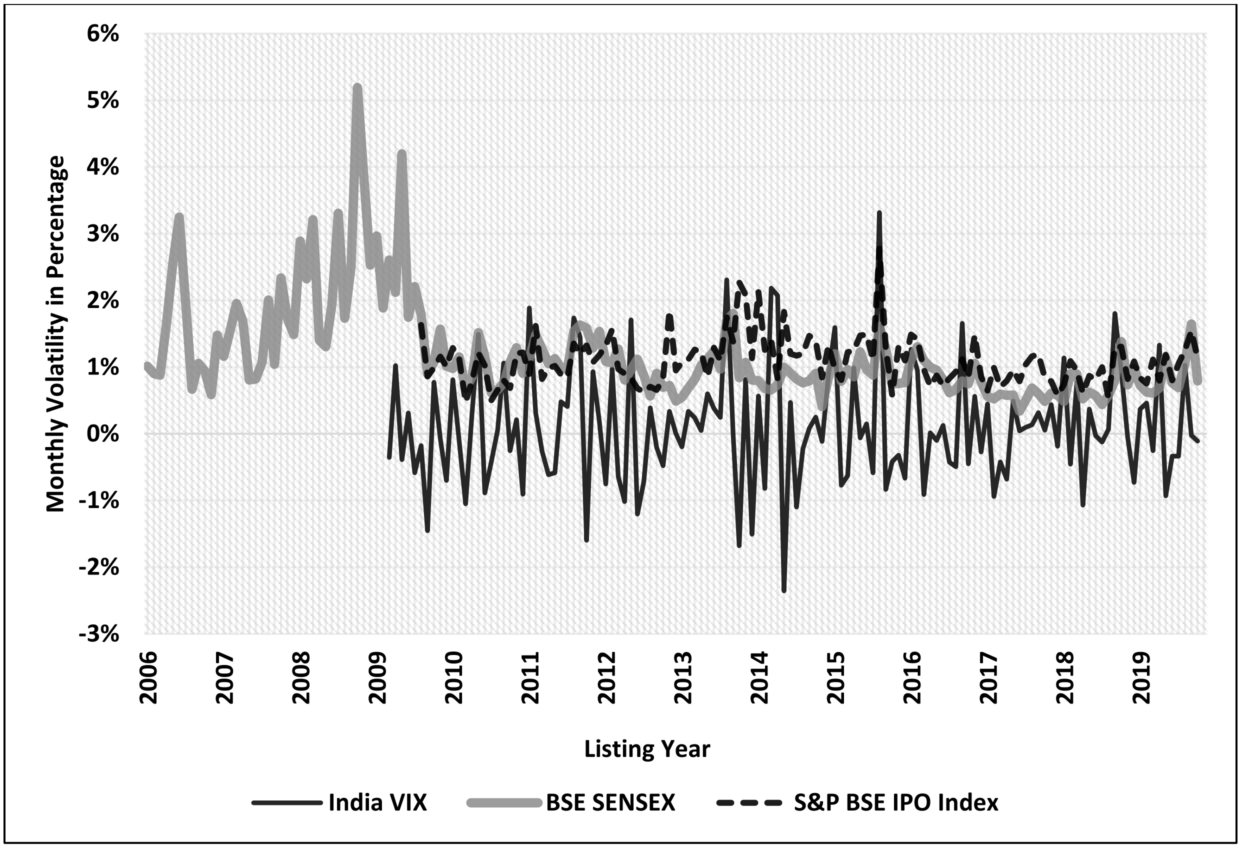

Figure 5. Expected Volatility of the Sensex (India VIX), Volatility of BSE SENSEX, and Volatility of S&P BSE IPO Index, 2006-2019. Volatility of SENSEX returns, and S&P IPO Index returns are calculated for each month. Similarly, the average monthly VIX is calculated. The dotted line represents the monthly volatility of S&P BSE IPO Index. The bold solid line represents the monthly volatility of BSE SENSEX and the thin solid line represents average monthly volatility (India VIX), respectively

Table 1: Sources of IPO Data, 2006-2019

Data Source	Sample Period	No. of IPOs	Underpriced IPOs in the total sample
PRIME and BSE Website	2006 – 2011 (Pre-regulation)	338	214 (64%)
PRIME and BSE Website	2012 – 2019 (Post Regulation)	451	339 (75%)
Total	**2006 - 2019**	**789**	**553 (70%)**

Table II: Description of Variables

Variable	Definition	Data Source
Post Regulation	Dummy variable set equal to 1 if the IPO is made in 2012 or later; else zero	NA
IPO Initial Return	Difference between the IPO's offer price and the closing market price on the first day of trading in the secondary market. A positive initial return is known as underpricing, whilst a negative initial return is known as overpricing. (Ibbotson et al, 1988; Ritter, 1998). This can also be measured using the 11th day or 21st day prices to remove the effect of price stabilization by underwriters or the trading rules. We use 21 day returns as our measure.	Bombay Stock Exchange
Monthly Volatility of Initial Returns	Variance of initial returns of all IPOs in a month	Bombay Stock Exchange, Prime IPO Database
Underwriter reputation	Equals one if the IPO is underwritten by top 10 underwriters in terms of market share at the time of the IPO and zero otherwise	Prime IPO Database
Log (Shares)	The logarithm of the shares issued in each IPO	Prime IPO Database
Tech dummy	Equals one if the firm is in a high-tech industry (biotech, computer equipment, electronics, communications, and general technology), and zero otherwise	CMIE Prowess
Venture capital dummy	Equals one if the firm received financing from venture capitalists prior to the IPO, and zero otherwise	Prime IPO Database
Log (Firm Age + 1)	The logarithm of the number of years since the firm was founded (at the time of the IPO)	CMIE Prowess
Log (Total Assets)	The natural log of total assets, a proxy for firm size	CMIE Prowess
Institutional Subscription (times)	Subscription by Qualified Institutional Buyers (QIB) in times, observable when the book building is open	Prime IPO Database
Retail Subscription (times)	Subscription by Retail Individual Investors (RII) in times, observable when the book building is open	Prime IPO Database
Non-Institutional Subscription (times)	Subscription by High-Net-worth Individuals (HNI) in times, observable when the book building is open	Prime IPO Database
Crisis dummy	Set equal to 1 if an IPO is issued in 2007 and 2008	Prime IPO Database

Table III: Descriptive Statistics on the Mean and Volatility of Initial Returns

Initial returns are measured as the percent difference between the aftermarket price on the listing day and the offer price. The summary statistics in this table reflect the periodic (2006-2011 and 2012-2019) averages, medians, and standard deviations. Skewness and Kurtosis are the measures of normality of the given data. Each period (2006-2011 & 2012-2019), the average, standard deviation, median, maximum and minimum values of initial returns as well as the proxy measures (for underwriters' ability to value firm), are calculated across all firms that went public during that period.

Panel A: 2006-2019; N=789	**Mean**	**Median**	**Std. Dev**
Listing Day Underpricing	14.092	7.322	27.072
Volatility of Listing Day Underpricing	25.127	18.597	22.62
11th Day Underpricing	17.24	10.672	42.224
Volatility of 11th Day Underpricing	38.801	27.775	45.557
21st Day Underpricing	18.359	10.177	44.273
Volatility of 21st Day Underpricing	46.846	32.348	47.803
ln (Shares)	15.478	15.409	0.845
ln (FirmAge+1)	2.544	2.557	0.411
ln (Total Assets)	7.463	7.491	1.542
ln (QIB Times Subscribed+1)	1.629	1.670	1.061
ln (HNI Times Subscribed+1)	1.871	1.749	1.382
ln (RetailTimesSubscribed+1)	.868	0.653	0.785
ln (Total Times Subscribed+1)	1.211	1.140	0.931
Panel B: 2006-2011; N=338	**Mean**	**Median**	**Std. Dev**
Listing Day Underpricing	21.992	20.042	37.814
Volatility of Listing Day Underpricing	36.88	27.868	23.879
11th Day Underpricing	15.984	11.237	45.839
Volatility of 11th Day Underpricing	39.344	32.448	28.243
21st Day Underpricing	11.938	7.614	45.309
Volatility of 21st Day Underpricing	44.124	33.913	34.796
ln (Shares)	16.069	15.964	.694
ln (FirmAge+1)	2.611	2.579	.412
ln (Total Assets)	8.386	8.279	.935
ln (QIB Times Subscribed+1)	1.585	1.531	1.157
ln (HNI Times Subscribed+1)	1.699	1.602	1.165
ln (RetailTimesSubscribed+1)	1.271	1.148	.829
ln (Total Times Subscribed+1)	1.668	1.477	.955

Panel C: 2012-2019; N=451	**Mean**	**Median**	**Std. Dev**
Listing Day Underpricing	8.437	5.114	12.924
Volatility of Listing Day Underpricing	17.048	12.991	17.772
11^{th} Day Underpricing	18.14	10.073	39.681
Volatility of 11^{th} Day Underpricing	38.435	26.504	54.393
21^{st} Day Underpricing	23.010	10.231	43.172
Volatility of 21^{st} Day Underpricing	48.683	31.933	55.013
ln (Shares)	15.056	15.017	.675
ln (FirmAge+1)	2.497	2.515	.406
ln (Total Assets)	6.803	6.602	1.556
ln (QIB Times Subscribed+1)	1.676	1.747	0.955
ln (HNI Times Subscribed+1)	2.051	2.048	1.568
ln (RetailTimesSubscribed+1)	0.580	0.376	0.610
ln (Total Times Subscribed+1)	0.884	0.613	0.765

Table III continued: Descriptive Statistics on Mean and Volatility of IPO Initial Returns

Panel D:

In each year, the average and standard deviation of monthly initial returns are measured across all firms that went public during that month in that year. Initial returns are measured as the percent difference between the aftermarket price on the 21st day and the offer price. The summary statistics in this table reflect the periodic (2006-2019, 2006-2011 and 2012-2019) time series of these cross-sectional averages and standard deviations, σ. Correl. is the correlation between the averages and standard deviations of these periodic returns

							Autocorrelation Lags					
		N	**Mean**	**Median**	**Std. Dev**	**Correl.**	**1**	**2**	**3**	**4**	**5**	**6**
Average IPO Initial Return	2006-2019	789	18.359	10.177	44.273		0.068	-0.015	-0.089	0.041	0.040	-0.018
Cross-Sectional Std. Dev of IPO initial return			46.846	32.348	47.803	0.6992	0.170	-0.075	-0.057	0.071	0.019	-0.041
Average IPO Initial Return	2006-2011	338	11.938	7.614	45.309		-0.127	-0.069	-0.064	-0.069	-0.142	-0.011
Cross-Sectional Std. Dev of IPO initial return			44.124	33.912	34.976	0.6353	0.095	-0.226	0.015	0.095	-0.272	-0.219
Average IPO Initial Return	2012-2019	451	23.010	10.231	43.172		0.195	-0.005	-0.146	0.118	0.157	0.007
Cross-Sectional Std. Dev of IPO initial return			48.683	31.933	55.013	0.8836	0.187	-0.037	-0.080	0.054	0.085	0.010
Average IPO Initial Return	2006-2019 (Excluding Crisis Period)		16.444	9.287	41.882		-0.302	0.158	-0.115	-0.093	0.052	0.029
Cross-Sectional Std. Dev of IPO initial return		647	45.085	31.252	48.220	0.1913	0.179	0.012	0.089	0.129	-0.242	-0.245

Table IV: Correlation Matrix of Key Variables

Panel A:

This table presents the correlation between key variables (as defined in table II), used in our analysis. The asterisk superscript ** represents significance at 5% level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Underpricing Listing Day	1.000													
(2) Underpricing 11 Days	0.831**	1.000												
(3) Volatility 11 Days	0.552**	0.387**	1.000											
(4) Underpricing 21 Days	0.744*	0.938**	0.309**	1.000										
(5) Volatility 21 Days	0.547**	0.391**	0.938**	0.326**	1.000									
(6) Post Regulation Dummy	-0.167**	-0.021	-0.414**	0.026	-0.353**	1.000								
(7) Underwriter Rank Dummy	0.020	-0.016	0.045	-0.031	-0.046	-0.135**	1.000							
(8) ln (Shares)	0.046	0.008	0.146**	-0.019	0.066	-0.373**	0.541**	1.000						
(9) Technology Dummy	0.088**	0.027	0.102**	0.007	0.087**	-0.152**	0.078**	0.069	1.000					
(10) Venture Capital Dummy	-0.035	-0.029	-0.012	-0.026	-0.059	0.075**	0.419**	0.104**	0.011	1.000				
(11) ln (Firm Age+1)	0.057	0.006	-0.007	0.000	-0.036	-0.066	0.217**	0.146**	0.013	0.136**	1.000			
(12) ln (Total Assets)	0.049	0.021	0.090**	-0.011	0.013	-0.350**	0.553**	0.635**	0.099**	0.230**	0.267**	1.000		
(13) Crisis Dummy	0.177**	0.099**	0.292**	0.064	0.276**	-0.541**	0.075**	0.142**	0.078**	-0.101**	0.055	0.166**	1.000	
(14) ln (Total Times Subscribed)	0.464**	0.381**	0.416**	0.332**	0.348**	-0.301**	0.357**	0.249**	0.120**	0.134**	0.209**	0.342**	0.221**	1.000

Panel B: This table shows correlations between the monthly averages and standard deviations of IPO initial returns and monthly average IPO market characteristics. The sample consists of IPOs between 2006 and 2019. Initial returns are estimated as the percentage difference between 21st day price and the offer price. See Table II for variable definitions. The *p*-values are in parentheses. The *t*-statistics use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscript ** represents significance at 5% level.

	Average Initial Return	**Average Initial Return**	**Average Initial Return**	**Std. Dev. of Initial Return**	**Std. Dev. of Initial Return**	**Std. Dev. of Initial Return**
	2006-2011 (including crisis bubble)	**2006-2011 (excluding crisis bubble)**	**2012-2019**	**2006-2011 (including crisis bubble)**	**2006-2011 (excluding crisis bubble)**	**2012-2019**
Average Underwriter reputation	-0.128 (0.317)	0.136 (0.402)	**-0.161** (0.136)	-0.290** (0.033)	-0.321 0.064	**-0.194** (0.085)
Average ln (Shares)	0.044 (0.730)	0.265 (0.099)	**-0.014** (0.899)	-0.178 (0.198)	-0.169 (0.339)	0.038 (0.738)
Percent Technology	0.045 (0.729)	-0.097 (0.550)	**-0.146** (0.177)	0.083 (0.550)	-0.059 (0.742)	**-0.078** (0.493)
Percent Venture Capital	-0.045 (0.725)	0.199 (0.217)	**-0.225**** (0.036)	-0.199 (0.149)	-0.038 (0.831)	**-0.224**** (0.046)
Average ln (Firm Age+1)	0.121 (0.346)	0.241 (0.134)	-0.209 (0.052)	-0.196 (0.155)	-0.363** (0.035)	**-0.056** (0.622)
Average ln (Total Assets)	0.160 (0.210)	0.404** (0.010)	**-0.117** (0.280)	-0.206 (0.134)	-0.334 (0.054)	**-0.133** (0.238)
Average ln (QIB Times Subscribed+1)	0.541** (0.000)	0.539** (0.000)	**-0.112** (0.401)	0.151 (0.277)	-0.156 (0.378)	**-0.239** (0.070)
Average ln (HNI Times Subscribed+1)	0.523** (0.000)	0.541** (0.000)	0.004 (0.974)	0.093 (0.503)	-0.214 (0.225)	**-0.205** (0.119)
Average ln (Retail Times Subscribed+1)	0.466** (0.000)	0.393** (0.012)	**-0.051** (0.637)	0.186 (0.179)	-0.122 (0.492)	**-0.151** (0.181)
Average ln (Total Times Subscribed+1)	0.532** (0.000)	0.562** (0.000)	**-0.056** (0.606)	0.102 (0.465)	-0.178 (0.314)	**-0.187** (0.096)

Table V: OLS Regressions of Initial Returns, 2006-2019

This table reports the results of OLS regressions. The dependent variable is the initial returns to IPOs. See Appendix A for description of variables. In the first regression (column 1) we include IPOs during the global financial crisis years i.e., 2007 and 2008. In the second regression we exclude them. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

	(1)	(2)
Post Regulation Dummy	-7.131**	-13.78**
	(-2.05)	(-2.15)
Underwriter Reputation Dummy	0.366	27.19***
	(0.08)	(-2.75)
ln (Shares)	-0.207	1.296
	(-0.16)	(-0.3)
Technology Dummy	4.750	5.312
	(1.87)	(-0.63)
Venture Capital Dummy	-2.473	-15.72
	(-0.70)	(-1.22)
ln (Firm Age + 1)	2.573	9.898
	(1.66)	(-1.57)
ln (Total Assets)	-0.286	-7.350**
	(-0.42)	(-2.68)
Global Financial Crisis Dummy	11.21**	
	(2.01)	
ln (QIB Times Subscribed + 1)		2.912
		(0.8)
ln (HNI Times Subscribed + 1)		2.731
		(1.02)
ln (Retail Times Subscribed + 1)		-4.839
		(-1.06)
Intercept	12.49	16.94
	(0.62)	(0.27)
Observations	789	647
Adj. R-squared	0.035	0.114

Table VI: MLE Regressions of Initial Return and Volatility, 2006-2019

This table reports the results of MLE regressions. The dependent variable in model 1 is the initial return. The dependent variable in model 2 & 3 is log of variance of the error from OLS regressions derived in table V. See Appendix A for description of variables. In the initial return regression (model 1) we exclude IPOs during the global financial crisis years i.e., 2007 and 2008. In the volatility regression (model 2) we include IPOs during the global financial crisis years i.e., 2007 and 2008. In the volatility regression (model 3) we exclude them. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

	Mean	**Variance**	**Variance**
	(1)	**(2)**	**(3)**
Post Regulation Dummy	-12.841**	-1.361***	-1.451***
	(-2.52)	(-3.45)	(-3.42)
Underwriter Reputation Dummy	26.57***	-0.116	0.127
	(2.93)	(-0.18)	(0.16)
ln (Shares)	2.396	0.565***	0.637***
	(1.61)	(5.68)	(5.74)
Technology Dummy	5.146	-0.621	-1.008
	(0.65)	(-1.12)	(-1.60)
Venture Capital Dummy	-16.547	-1.643*	-1.358
	(-1.40)	(-1.79)	(-1.32)
ln (Firm Age + 1)	10.250*	0.715*	0.615
	(1.76)	(1.79)	(1.36)
ln (Total Assets)	-7.542***	-0.523***	-0.616***
	(-3.02)	(-3.08)	(-3.10)
Global Financial Crisis Dummy		0.376	
		(0.99)	
ln (QIB Times Subscribed + 1)	2.982	0.172	0.136
	(0.87)	(0.72)	(0.51)
ln (HNI Times Subscribed + 1)	2.742	0.068	0.065
	(1.09)	(0.39)	(0.35)
ln (Retail Times Subscribed + 1)	-4.795	0.268	0.321
	(-1.12)	(0.89)	(0.93)
Intercept	19.190	1.333	1.383
	(13.93)	(15.03)	(13.56)
Observations	647	789	647
Log Likelihood	-424.213	-192.784	-160.364

Table VII: Propensity Score Matching of Initial Returns

In this table, we compare the initial returns of anchor backed (=1) and Non-Anchor backed (=0) initial public offerings (IPOs) using a nearest neighbour propensity matching procedure. The propensity score is estimated during 2009–2011 (the time period elapsed between the introduction of AI legislation and the introduction of the pre-opening trading) and 2012-2019 (Post AI and pre-opening trading legislations) respectively, using controls such as no. of shares, firm age, firm size [total assets], technology dummy and subscription by institutional and retail investors) in a logit regression analysis. The t-statistics are in parentheses. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

2009-2011	**Mean %**	**Difference % (Anchor & Non-Anchor)**
Initial Returns % (Anchor Backed IPOs)	24.10	25.63***
		(4.52)
Initial Returns % (Non-Anchor Backed IPOs)	-1.53	
2012-2019	**Mean %**	**Difference % (Anchor & Non-Anchor)**
Initial Returns % (Anchor Backed IPOs)	6.23	-34.29*
		(-1.91)
Initial Returns% (Non-Anchor Backed IPOs)	40.82	

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Table VIII: Difference in Difference Estimation of Initial Returns with Covariates

This Table reports the difference in difference estimation of initial returns of anchor-backed and non-anchor-backed initial public offerings (IPOs. The regression equation is: UP = b_0 + b_1Post regulation Dummy + b_2Anchor Dummy + b_3DID + $b_i(X_j)$. The dependent variable in column 1 is the initial return measured using listing day closing price and that in column 2 is initial return measured using 21st day closing price. The parameters are post regulation Dummy, which is a dummy variable for IPOs launched before/after 2012; Anchor Dummy and DID, which is the product of post regulation Dummy and Anchor Dummy; and X_i are covariates. The regressions include industry and time fixed effects. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

	(1)	**(2)**
Post Regulation Dummy	14.04**	75.83***
	(2.34)	(4.09)
Anchor Backed IPO Dummy	14.63**	26.13
	(2.05)	(1.55)
DID	-14.34*	-35.92*
	(-1.68)	(-1.80)
Underwriter Reputation Dummy	-0.456	
	(-0.05)	
ln (Shares)	3.947	4.683
	(1.26)	(0.61)
Tech Dummy	-0.642	-10.39
	(-0.20)	(-1.32)
Venture Capital Dummy	-2.815	-26.26
	(-0.36)	(-1.41)
ln (Firm Age+1)	0.764	-6.356
	(0.15)	(-0.69)
ln (Total Assets)	-0.534	2.794
	(-0.31)	(0.69)
ln (Retail Times Subscribed+1)	4.722*	4.227
	(1.85)	(0.67)
Intercept	-64.09	-77.80
	(-1.19)	(-0.69)
Observations	647	647
R-Squared	0.112	0.191

Table IX: Difference in Difference Estimation of Volatility of Initial Returns with Covariates

This Table reports the difference in volatility of initial returns between anchor-backed and non-anchor-backed initial public offerings (IPOs) using the difference-in-differences (DiD) estimation procedure. The regression equation is: Log Var UP = b_0 + b_1Post regulation Dummy + b_2Anchor Dummy + b_3DID + $b_i(X_j)$. The dependent variable in column 1 is the volatility of initial return measured using 21st day closing price. The parameters are post regulation Dummy, which is a dummy variable for IPOs launched before/after 2012; Anchor Dummy and DID, which is the product of post regulation Dummy and Anchor Dummy; and X_i are covariates. The regressions include industry and time fixed effects. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

Post Regulation Dummy	1.866
	(1.85)
Anchor Backed IPO Dummy	0.488
	(0.34)
DID	-2.856*
	(-1.69)
ln (Shares)	0.235
	(0.62)
Tech Dummy	-0.495
	(-1.22)
Venture Capital Dummy	0.219
	(0.26)
ln (QIB Times Subscribed+1)	-0.538
	(-1.40)
ln (HNI Times Subscribed+1)	0.188
	(0.75)
ln (Retail Times Subscribed+1)	-0.0646
	(-0.14)
Intercept	3.231
	(0.52)
Observations	572
R-Squared	0.118

Table X: OLS Regression of Volatility of Initial Returns of Anchor Backed IPOs

This table reports the results of OLS regression. The dependent variables are the natural log of variance of the error from OLS regressions of initial returns measured using 21st day prices. The independent variables are the product of Post Regulation Dummy, which is a dummy variable for IPOs launched after 2012 and anchor backed Dummy, a dummy variable set equal to 1 for firms that are backed by anchor investors, and the covariates used in earlier regressions and defined in Table II. The regression includes industry and time fixed effects (coefficient unreported). The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * represent significance at the 1%, 5% and 10% levels.

	(1)
Post Regulation Dummy * Anchor Backed Dummy	-0.876*
	(-1.900)
ln (Shares)	0.521
	(1.622)
Tech Dummy	-0.749**
	(-2.033)
ln (Firm Age+1)	0.220
	(0.415)
ln (Total Assets)	-0.289
	(-1.401)
ln (HNI Times Subscribed+1)	-0.0497
	(-0.317)
ln (Retail Times Subscribed+1)	0.858**
	(2.239)
Intercept	-0.832
	(-0.194)
Observations	572
R-Squared	0.214

Table XI: OLS Regression of Volatility of Initial Returns of Young Firms

This table reports the results of OLS regression. The dependent variables are the natural log of variance of the error from OLS regressions of initial returns measured using 21st day prices and listing day prices respectively. The independent variables are the product of Post Regulation Dummy, which is a dummy variable for IPOs launched after 2012 and Young Firm Dummy, a dummy variable set equal to 1 for firms that are in the bottom quartile of the entire sample in terms of firm age, and the covariates used in earlier regressions and defined in Table II. The regression includes time fixed effects (coefficient unreported). The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * represent significance at the 1%, 5% and 10% levels.

	(1) **Variance 21st Day**	**(2)** **Variance Listing Day**
Post Regulation Dummy * Young Firm Dummy	-1.468**	-0.873*
	(-2.388)	(-1.784)
Underwriter Reputation Dummy	0.544	-0.614
	(0.534)	(-0.758)
ln (Shares)	0.595	
	(1.605)	
Tech Dummy	-0.678*	-0.456
	(-1.795)	(-1.482)
Venture Capital Dummy	0.219	-0.789
	(0.243)	(-1.094)
ln (FirmAge+1)	-1.385**	-0.435
	(-2.160)	(-0.842)
ln (Total Assets)	-0.219	-0.132
	(-1.036)	(-0.884)
ln (Retail Times Subscribed+1)	0.0412	1.017***
	(0.139)	(4.232)
Intercept	2.562	8.416***
	(0.420)	(4.060)
Observations	647	647
R-squared	0.139	0.300
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes

Table XII: Change in Volatility of Initial Returns of Young Firms

This table reports the results of estimation of change in the Volatility (variance) from two years before 2012 to two years after implementation. The regression equation is: $\triangle$ Log (Var IR_t) = β_0 + β_1 (Post Regulation Dummy) + β_2 (Young Firm Dummy) + β_3 (Post Regulation * Young frim Dummy) + βi (Xjt) + βj ($\triangle$Xjt). The parameters are Post Regulation Dummy, which is a dummy variable for IPOs launched after 2012; Young Firm Dummy, a dummy variable set equal to 1 for firms that are in the bottom quartile of the entire sample in terms of firm age and the product of Post Regulation Dummy and Young Firm Dummy; and Xi are covariates. $\triangle$ is the change in covariates between 2010 and 2014. Model 2 incorporates the absolute values of covariates along with changes in the respective covariates. The t statistics are in parentheses. The asterisk superscript * represents significance at the 10% level.

	(1) **△ Log Variance** **(-2, +2)**	**(2)** **△ Log Variance** **(-2, +2)**
Post Regulation Dummy	0.481	0.389
	(0.919)	(0.597)
Young Firm Dummy	0.452	-0.270
	(0.501)	(-0.276)
Post regulation * Young Firm Dummy	-1.946*	-2.109*
	(-1.834)	(-1.963)
Tech Dummy	-0.543	-0.449
	(-1.231)	(-1.008)
Venture Capital Dummy	-0.0451	0.496
	(-0.0496)	(0.504)
Underwriter Rank Dummy		0.267
		(0.238)
ln (Total Assets)		-0.0468
		(-0.206)
ln (Retail Times Subscribed+1)		0.0804
		(0.217)
△ln (Shares)	-3.795	-4.499
	(-0.818)	(-0.951)
△ln (Firm Age+1)	-0.925	-1.001
	(-1.060)	(-1.129)
△ln (Total Assets)	-0.0237	0.120
	(-0.0269)	(0.136)
△ln (Retail Times Subscribed+1)	0.00674	0.0387
	(0.0624)	(0.354)
Intercept	7.009***	11.06***
	(13.37)	(3.479)
Observations	647	647
Adj. R-squared	0.124	0.174

Table XIII: Maximum Likelihood Estimation

This table presents the results of Maximum Likelihood Estimation regressions. The dependent variables in model 1, 2 and 3 are the mean and variance of listing day and 21 days initial return, respectively. The regressions control for monthly time series (TS) and cross sectional (CS) volatility of the market. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% levels.

	Listing Day IR	**Listing Day-Variance**	**21 Day-Variance**
Post Regulation Dummy	-9.846*	-1.72***	-0.021**
	(-1.67)	(-3.80)	(-2.05)
Underwriter Reputation Dummy	-1.437	0.423***	-0.003
	(-0.71)	(2.84)	(-0.09)
ln (Shares)	1.337	0.546***	0.008***
	(0.81)	(4.53)	(2.88)
Technology Dummy	0.501	-0.547*	-0.003
	(0.11)	(-1.66)	(-0.32)
Venture Capital Dummy	3.437	-0.130	0.006
	(0.95)	(-0.49)	(0.79)
ln (Firm Age + 1)	6.829	0.821*	-0.004
	(1.14)	(1.67)	(-0.35)
ln (Total Assets)	-4.902**	-0.622***	-0.011**
	(-1.97)	(-3.28)	(-2.20)
ln (QIB Times Subscribed + 1)	4.622	-0.584	-0.012
	(1.25)	(-0.20)	(-1.62)
ln (HNI Times Subscribed + 1)	2.148	0.210	0.008
	(0.79)	(1.04)	(0.09)
ln (Retail Times Subscribed + 1)	-3.343	0.134	
	(-0.76)	(0.38)	
BSE SENSEX (TS), Log (S^2_{t-1})	301.676	-75.770	0.132
	(0.420	(-1.43)	(0.09)
BSE SENSEX (CS), Log (C^2_{t-1})	410.033	77.941*	2.312**
	(0.72)	(1.86)	(2.03)
Intercept	19.775***	1.421***	0.039***
	(14.07)	(13.71)	(14.07)
Observations	647	647	647
Log Likelihood	-435.933	-166.425	179.456

Table XIV: Difference in Difference Estimation

This Table reports the difference in difference estimation of underpricing between anchor-backed and non-anchor-backed initial public offerings (IPOs). The regression equation is: UP = b_0 + b_1Post regulation Dummy + b_2Anchor Dummy + b_3DID + $b_i(X_j)$. The dependent variables in columns 1 and 2 are the initial returns measured using listing day closing price and 21st day closing price. The parameters are post regulation Dummy, which is a dummy variable for IPOs launched before/after 2012; Anchor Dummy and DID, which is the product of post regulation Dummy and Anchor Dummy; and X_i are covariates. The regressions control for monthly cross sectional (CS) volatility of BSE Sensex. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

	(1)	**(2)**
Post Regulation Dummy	15.24**	53.29***
	(2.197)	(3.578)
Anchor Backed IPO Dummy	13.95*	28.12*
	(1.893)	(1.729)
DID	-14.99*	-32.70*
	(-1.672)	(-1.672)
Underwriter Reputation Dummy	0.615	16.59*
	(0.0551)	(1.754)
ln (Shares)	4.176	12.33*
	(1.175)	(1.714)
Tech Dummy	0.433	-20.79
	(0.123)	(-1.422)
Venture Capital Dummy		-9.413
		(-1.273)
ln (Total Assets)	-0.0757	
	(-0.0299)	
ln (Firm Age +1)	-5.270	
	(-1.308)	
ln (Retail Times Subscribed+1)	4.820*	2.349
	(1.728)	(0.373)
BSE SENSEX(CS), Log (C^2_{t-1})	-126.7	1,647*
	(-0.251)	(1.725)
Intercept	-68.48	-246.4*
	(-1.205)	(-1.934)
Observations	647	647
R-squared	0.119	0.151

Table XV: Difference in Difference Estimation of Volatility of Initial Returns

This Table reports the difference in difference estimation of volatility of underpricing between anchor-backed and non-anchor-backed initial public offerings (IPOs). The regression equation is: Log (Var(UP)) = $b_0 + b_1$Post regulation Dummy + b_2Anchor Dummy + b_3DID + $b_i(X_j)$. The dependent variable is the log variance of initial returns. The parameters are post regulation Dummy, which is a dummy variable for IPOs launched before/after 2012; Anchor Dummy and DID, which is the product of post regulation Dummy and Anchor Dummy; and X_i are covariates. The regressions control for monthly time series and cross sectional (CS) volatility of BSE Sensex. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

	(1)
Post Regulation Dummy	-0.0216
	(-1.157)
Anchor Backed IPO Dummy	-0.00924
	(-0.598)
DID	0.0399**
	(1.997)
Underwriter Reputation Dummy	0.00526
	(0.530)
ln (Shares)	0.0106
	(1.316)
Tech Dummy	-0.00728
	(-0.837)
Venture Capital Dummy	-0.000649
	(-0.0916)
ln (FirmAge+1)	-0.000786
	(-0.0659)
ln (Total Assets)	-0.0123**
	(-2.188)
ln (QIB Times Subscribed + 1)	-0.0187**
	(-2.211)
ln (HNI Times Subscribed + 1)	0.00806
	(1.457)
ln (Retail Times Subscribed + 1)	0.0112
	(1.250)
BSE SENSEX (TS), Log (T^2_{t-1})	-0.447
	(-0.266)
BSE SENSEX (CS), Log (C^2_{t-1})	2.084
	(1.640)
Intercept	-0.0232
	(-0.164)
Observations	647
R-squared	0.270

Table XVI: Difference in Difference Estimation of Long-term Volatility of IPO Initial Returns with Covariates.

This Table reports the difference in difference estimation of long-term volatility of anchor-backed and non-anchor-backed IPOs. The regression equation is: SD = $\alpha + \beta_1$ (Post-regulation Dummy) + β_2 (Anchor Dummy) + β_3 DID + β_i (X_j). The dependent variable is the standard deviation of daily stock returns of IPO firms over 130 days from the date of listing. The parameters are post regulation Dummy, which is a dummy variable equal to 1 for IPOs launched after 2012; Anchor Dummy and DID, which is the product of post regulation Dummy and Anchor Dummy; and X_i are covariates. The model controls for the volatility of BSE Sensex measured over 130 days from the date of listing. The *t*-statistics, in parentheses use White's (1980) heteroscedasticity-consistent standard errors. The asterisk superscripts ***, ** and * denote significance at the 1%, 5% and 10% respectively.

	SD 130 Days
Post Regulation Dummy	0.490***
	(2.88)
Anchor Backed IPO Dummy	0.251
	(1.39)
DID	-0.375*
	(-1.72)
ln (Shares)	0.0924
	(1.10)
Tech Dummy	-0.173*
	(-1.72)
Venture Capital Dummy	-0.0744
	(-0.39)
ln (Firm Age+1)	-0.104
	(-0.90)
ln (Total Assets)	0.0344
	(0.86)
ln (QIB Times Subscribed+1)	-0.151
	(-1.54)
ln (HNI Times Subscribed+1)	0.111*
	(1.82)
ln (Retail Times Subscribed+1)	0.0650
	(1.07)
BSE SENSEX (130 Days)	16.84
	(1.17)
Intercept	-1.750
	(-1.26)
Observations	635
R-Squared	0.190