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Auctions versus bookbuilding: The effects of IPO regulation in Japan

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Abstract

We analyze a regulatory change in the Japanese IPO market that created an abrupt shift from hybrid price-discriminatory auctions to bookbuilding. We find that bookbuilding leads to higher underpricing than hybrid price-discriminatory auctions. Furthermore, we find evidence that price accuracy tends to be higher for auctions than for bookbuilding. The results hold under a variety of OLS specifications and with regression discontinuity designs exploiting the abrupt change of the regulation.

KEYWORDS
auction, bookbuilding, initial public offering, IPO regulation

JEL CLASSIFICATION
G30, G32, G38, G12

1 | INTRODUCTION

Bookbuilding is currently the predominant price discovery method for initial public offerings (IPOs) in most markets worldwide. It has superseded other methods in almost all the markets in which it was introduced (Jagannathan et al., 2015). In the bookbuilding process, an investment bank acts as underwriter and has pricing and share allocation discretion. Bookbuilding is generally found to lead to substantial share price increases on the first day of trading (the terms "underpricing," "initial return," and "return on the first day of trading" are interchangeable). Loughran and Ritter (2002) show that IPOs in the US between 1990 and 1998 left more than USD 27 billion on the table, indicating a sizable wealth loss by issuers.

Auctions, another price discovery method, are discussed in the literature as an alternative to bookbuilding and are widely used to price other securities (e.g., government bonds). Several countries have used auctions in different forms to price and allocate IPOs at some point in time. There is some empirical evidence that auctions lead to lower underpricing than bookbuilding (e.g., Beierlein & Kato, 2003; Derrien & Womack, 2003; Kaneko & Pettway, 2003).

The Japanese IPO market provides a unique institutional setting to analyze two different IPO price discovery methods. We use linear regressions with varying time windows and regression discontinuity designs to exploit a regulatory change from auctions to bookbuilding. Until 1997, Japanese regulation allowed only hybrid price-discriminatory auctions to price and allocate IPOs. On September 1, 1997, bookbuilding was introduced as an alternative method. Interestingly, hybrid price-discriminatory auctions have not been used since the introduction of bookbuilding.

While the regulatory change provides a good opportunity to analyze the different IPO mechanisms, the fact that bookbuilding and auctions appear at different time points (before September 1997 vs. thereafter) makes the issue non-trivial. To ensure that our results are not driven by the time dimension rather than the change in regulation, we provide a whole battery of analyses. (1) We vary the time window from which observations are included in OLS regressions, analyzing how far the results are robust to including observations closer and further from the regulatory change, (2) we implement a regression discontinuity design with a global strategy; that is, we include observations far from the regulatory change but allow for a variety of different polynomial specifications of time to account for the time dimension, and (3) we implement a regression discontinuity design with a local strategy; that is, observations far from the regulatory change are excluded (for different bandwidths) and local linear regressions are conducted (with different kernels, partly assigning more weight to the observations closer to the regulatory change). All these approaches in isolation have advantages and disadvantages; taken together they give a good picture of what is happening and ensure that the results are robust.

We analyze two research questions. First, we analyze whether and how initial returns differ between bookbuilding and auctions. Second, we analyze whether and how price accuracy in the aftermarket differs between the two IPO methods.

We find robust empirical evidence that underpricing in Japan is higher for bookbuilding than for hybrid price-discriminatory auctions. The results of a multiple linear regression analysis indicate that bookbuilding leads to initial returns that are substantially (up to 38 percentage points) higher. The global strategy of the regression discontinuity design confirms these findings. However, the estimates are sensitive to the order of the polynomial time trend. The local strategy of the regression discontinuity design also indicates that there is a difference in underpricing but at a lower level (for the lowest considered bandwidths, which have a relatively low number of observations, the coefficients are of similar magnitudes as for higher bandwidths but without being statistically significant). The magnitudes are economically relevant, with average wealth losses for issuers using bookbuilding of several million USD, as compared to those using auctions.

The second research question considers aftermarket price accuracy. This is an important analysis, because it can shed light on whether potentially higher underpricing under bookbuilding is beneficial for the issuer (arising from the need to incentivize information acquisition; in this case, aftermarket price accuracy should be higher for bookbuilding) or detrimental (for instance, due to a conflict of interest between issuer and underwriter; in that case, aftermarket price accuracy should be equal for both methods, or higher for auctions). We find that hybrid price-discriminatory auctions lead to higher price accuracy in the secondary market than bookbuilding. This finding is again robust to using different methodologies (with statistically insignificant coefficients for local regression discontinuity analyses with low bandwidths and correspondingly low numbers of observations).

We believe that the contribution of this paper is substantial, despite the fact that the Japanese regulatory change has already been analyzed by Kaneko and Pettway (2003) for underpricing and by Pettway et al. (2008) for price accuracy. These studies conduct simple linear regressions at one point in time. While this was the standard methodology when the studies were carried out (the use of the other methods should thus not be seen as criticism of the early contributions), the methodology can have serious drawbacks. If the results are driven by one or very few events that happened within the timeframe for the OLS analysis, considering a variety of different timeframes can mitigate this problem (this is one of our analyses). However, underpricing could potentially also be driven by time in different ways, for example, by an unobserved factor changing itself over time. To avoid this, regression discontinuity designs can be employed. Local versions focus on observations around the regulatory change, while a global version accounts for time by including polynomial time terms in the regressions. We conduct all these analyses, with similar results. This is the major contribution of our paper.

Another contribution of our paper is that we analyze absolute abnormal buy-and-hold returns instead of volatility as a measure of price accuracy (yet another contribution is that we have additional data available for the analysis). Volatility is a measure of risk that focuses on short-term changes (usually from day to day). This is not very relevant for issuers or initial investors, who are often invested for longer periods of time. Absolute abnormal buy-and-hold returns may be considered a better measure of price accuracy from the viewpoint of the issuer or the initial investors, because this measure is relevant if one considers the selling of shares after a while (e.g., one year after the IPO). Aftermarket price accuracy proxied by absolute abnormal returns has not yet been analyzed in the setting of the Japanese regulatory change.

The remainder of the paper is organized as follows. Section 2 discusses the related literature. In Section 3, we describe the institutional setting of the Japanese IPO market. Section 4 introduces the methodology. The data is described in Section 5. Our results on underpricing are shown in Section 6 and the results on price accuracy in Section 7. Section 8 concludes.

2 | RELATED LITERATURE

Underpricing, defined as the initial return of IPOs, was first documented by Logue (1973), Stoll and Curley (1970), and Reilly (1973). The finding that IPOs exhibit a large first-day return is robust. Ritter (2003) summarizes the average underpricing of IPOs in 38 countries for periods between 1960 and 2000. IPOs in all 38 countries are underpriced with average initial returns ranging from 5.4% in Denmark (1984–1998) to 256.9% in China (1990–2000). A more recent overview of underpricing for Asia-Pacific markets is provided by Albada and Yong (2019), who report average initial returns from 15.8% in Hong Kong (1980–2013) to 118.4% in China (1990–2013). For Japan, they report an average underpricing of 41.7% for the period 1970 to 2013.

The strand of literature most closely related to our paper is that relating the IPO mechanism (the IPO price discovery method) to underpricing. There are a few studies comparing underpricing between IPO mechanisms (in particular between bookbuilding and auctions) in different parts of the world and very few studies comparing aftermarket price accuracy. Empirical research indicates that auctions lead to lower underpricing than bookbuilding. Kaneko and Pettway (2003) report for hybrid price-discriminatory auctions in Japan a much lower average initial return between January 1993 and September 1997 than for bookbuilding for the period October 1997 to December 2001. Following up on this, Pettway et al. (2008) investigate aftermarket stock price volatility (as a proxy of price accuracy), finding that auctions lead to less volatile aftermarket prices than bookbuilding. Based on a cross-country comparison, Beierlein and Kato (2003) find that initial returns are higher and price accuracy is lower for US bookbuilding than for Japanese hybrid price-discriminatory auctions. Further, they find an indication that price accuracy of auctions is higher than of bookbuilding.

Besides Japan, good institutional settings to compare IPO auctions and bookbuilding are rare. In Taiwan, a fixed-price method, hybrid price-discriminatory auctions and hybrid bookbuilding partly co-existed (hybrid here refers to a fixed-price offer with up to 50% allotment to a bookbuilding or auction offering). Huang et al. (2017) show that hybrid bookbuilding leads to higher initial returns than hybrid price-discriminatory auctions and that the auction method outperforms hybrid bookbuilding in the long run. Derrien and Womack (2003) analyze French IPO data and find that uniform-price auctions are associated with lower underpricing than bookbuilding. In India, a regulatory change replaced a version of bookbuilding in which underwriters have share allocation discretion with a version in which underwriters do not have share allocation discretion (but keep the flexibility to set a price below the market clearing price). The version without share allocation discretion is essentially a so-called dirty Dutch auction (Bubna & Prabhala, 2011). The regulatory change took place in November 2005. In addition to these two methods, a fixed-price method was available to issuers at any time. Bubna and Prabhala (2011) analyze data from 34 bookbuilding IPOs

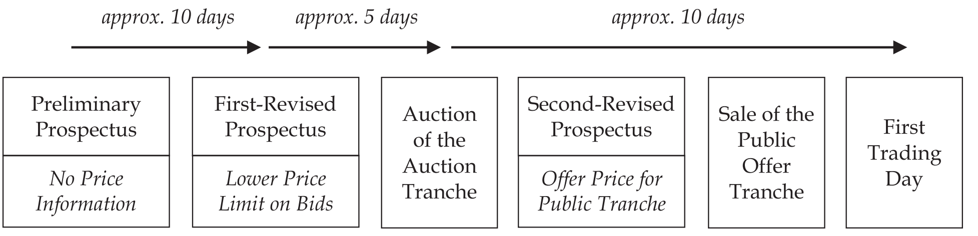

FIGURE 1 Japanese hybrid price-discriminatory auction process

before the regulatory change, and 58 after the regulatory change, jointly with 16 fixed-price IPOs before and 16 after the regulatory change. Underpricing was higher with the earlier version of bookbuilding than with the auction-type bookbuilding. However, underpricing of fixed-price IPOs decreased even more during this time period. The results thus reverse when they do not consider the bookbuilt IPOs in isolation but instead employ a difference-in-difference analysis with the fixed-price IPOs as control group. Although there are only very few observations available, Pukthuanthong et al. (2007) investigate the difference in underpricing between bookbuilding and dirty Dutch auctions in the US. Their findings suggest that bookbuilding leads to higher underpricing.

3 | INSTITUTIONAL SETTING IN THE JAPANESE IPO MARKET

3.1 | Hybrid price-discriminatory auction

After a political scandal in 1989, regulation ensured that IPOs used a hybrid price-discriminatory ("pay-what-you-bid") auction. There were several regulatory changes in the hybrid price-discriminatory auction method during the period 1989–1992. The data for our paper starts in 1993 and does not further address these regulatory changes. From 1993 onwards, the regulatory environment was stable (for details, see Pettway & Kaneko, 1996; Kaneko & Pettway, 2003).

The hybrid price-discriminatory auction method required issuers to offer at least 50% of shares on sale in an auction tranche. After the auction, the remaining shares were sold in a public offer tranche. The hybrid price-discriminatory auction was thus a two-step procedure, consisting of an auction (the auction tranche) and a fixed-price offering (the public offer tranche).

The auction process started with the publication of a preliminary prospectus without any price information. About 10 days after the preliminary prospectus was published, the lower price limit on bids in the auction was defined. The underwriter selected (usually three) comparable companies and calculated an expected offer price for the IPO firm. The lower price limit on bids was then set 15% below the expected offer price and published in the first-revised prospectus. A one-day price-discriminatory auction took place around 5 days later. On the day of the auction, all bids were aggregated, and the shares were allocated. The highest bidders were served first until all shares were allocated or the lower price limit on bids was reached. Japanese regulation strictly forbade the participation of firm insiders and limited the number of shares that one investor could buy in the auction tranche to no more than 5000.

Shortly after the auction, the second-revised prospectus was published which included the offer price for the public offer tranche. The underwriter set the offer price for the public offer tranche but was constrained by the weighted average of successful bids in the auction tranche as an upper limit and by the lower price limit on bids in the auction tranche as a lower limit. The public offer tranche was a formal underwritten offering and the underwriter had allocation discretion. There was also a quantity restriction of 5000 shares per investor in the public offer tranche.

The number of days between the auction and the first trading day in our sample was between 6 and 15 days. Figure 1 summarizes the auction process (for more details, see Kaneko & Pettway, 2003; Kutsuna & Smith, 2004; Kerins et al., 2007).

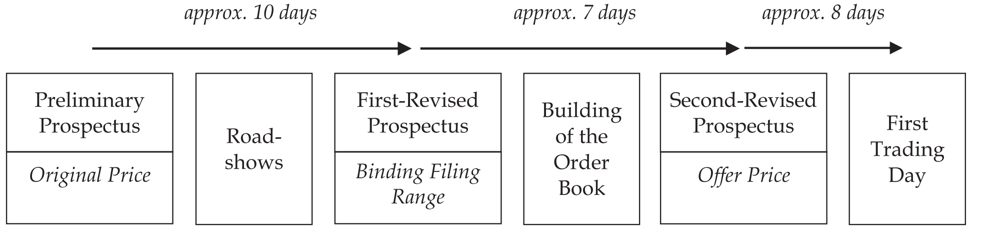

FIGURE 2 Japanese bookbuilding process

3.2 | Bookbuilding

On September 1, 1997, Japanese regulators introduced the bookbuilding method as an alternative to hybrid price-discriminatory auctions. Price-discriminatory auctions were still possible but no longer used.[1]

The bookbuilding process started with the publication of a preliminary prospectus that included an original price defined by the underwriter and the issuer. In the following ten days, roadshows with selected investors took place. After these roadshows, the first-revised prospectus was published that defined a filing range. In the Japanese bookbuilding method, this filing range was binding for the underwriter which means that the final offer price had to be within this range. In the following approximately seven days, the order book was built. Typically, around 40–70 institutions submitted indications of interest, which helped the underwriter to assess market demand. Once this process was completed, the underwriter defined the final offer price, which was announced in the second-revised prospectus. The underwriter determined the percentage of shares sold to institutional investors and allocated the shares. Usually, about 20–30 percent of shares were sold to institutional investors. Approximately eight days later, the stocks were traded at the stock exchange for the first time. The Japanese bookbuilding process is summarized in Figure 2 (a similar figure can be found in Kutsuna et al., 2009; for details on this bookbuilding process, see Kaneko & Pettway, 2003; Kutsuna et al., 2009).

4 | METHODOLOGY

4.1 | Hypotheses

We consider two null hypotheses. The first is the following:

- Null hypothesis 1: There is no difference in underpricing between hybrid price-discriminatory auctions and bookbuilding.

The tests we consider are two-sided, but the alternative hypothesis that seems most convincing is that bookbuilding leads to higher underpricing than auctions (in line with the empirical evidence provided by Kaneko & Pettway, 2003; Beierlein & Kato, 2003).

The second null hypothesis we consider is the following:

- Null hypothesis 2: There is no difference in price accuracy in the secondary market between the two methods.

[1] Bookbuilding was officially introduced on September 1, 1997. The first listing took place on September 30, 1997. One IPO auction took place after thereafter (on October 7, 1997). We nevertheless define September 30, 1997, as the date of the policy discontinuity, since there was only one single auctioned IPO thereafter.

There are arguments for deviations in both directions. On the one hand, there is a theoretical argument. In the model by Sherman (2005), there is higher underpricing but also higher aftermarket price accuracy for bookbuilding. In her model, bookbuilding leads to underwriters having control over information production by investors via pricing and share allocation discretion. According to Sherman (2005), "more information production leads to more underpricing, a higher probability that the firm's true value is reflected in the initial trading price, and a lower probability of aftermarket price shifts". On the other hand, empirical evidence points in the other direction (Beierlein & Kato, 2003; Pettway et al., 2008).[2]

4.2 | Variable definitions

The dependent variables are underpricing and price accuracy. They are explained in Sections 4.2.1 and 4.2.2. The covariates (control variables) are described in Section 4.2.3.

4.2.1 | Underpricing

Underpricing y_I, in percentage terms, is defined as the first-day return based on the offer price OP and the closing share price on the first trading day CP of IPO firm I:

$$y_I = \frac{CP_I - OP_I}{OP_I} * 100$$

For bookbuilding, the offer price is equal to the offer price published in the second-revised prospectus. For the auction, there is an auction tranche and a public offer tranche with different offer prices. The offer price of the auction tranche is equal to the weighted average of successful bids in the auction. For the public offer tranche, the offer price is equal to the offer price published in the second-revised prospectus. Hence, underpricing for auctions is calculated based on the weighted average offer price of the two tranches.

4.2.2 | Price accuracy

We proxy price accuracy by absolute abnormal returns. As it can be argued that summing up abnormal returns over longer horizons is a source of bias, we use absolute abnormal buy-and-hold returns over a 12-month aftermarket period. We use the market-capitalization-weighted JASDAQ index as benchmark, constituted by all stocks traded at the JASDAQ stock exchange (Over-the-Counter market before 2004). Absolute abnormal buy-and-hold returns $y_{I,t}$, in percentages, of IPO firm I for a time window of 12 months or until delisting (t) are calculated as

$$y_{I,t} = \left| \left(\frac{P_t - P_0}{P_0} - \frac{B_t - B_0}{B_0} \right) * 100 \right|$$

where P_t equals the closing share price of the IPO stock t months after the IPO; P_0 equals the closing share price of the IPO stock on the first trading day; B_t equals the closing price of the benchmark stock index t months after the IPO; and B_0 equals the closing price of the benchmark stock index on the IPO date.

[2] Boulton et al. (2021) show that firms with a Wikipedia article when they go public experience higher underpricing than firms without one. This could be interpreted as evidence that information asymmetries are not the main driver of underpricing.

4.2.3 | Covariates

We use six covariates to control for firm characteristics, IPO specific factors and market conditions. Appendix B provides the formulas for their calculations.

Firm age (log): Firm age is calculated as the logarithm of the difference between the founding date and the IPO date.

Expected issue size (log): Following Kaneko and Pettway (2003), we calculate the log expected issue size as the logarithm of the product of the expected offer price and the total number of shares on sale in the IPO (the expected issue size is taken, because the actual issue size is endogenous to underpricing; see Habib & Ljungqvist, 2001). The expected offer price for the bookbuilding method is equal to the average of the upper and lower limit of the filing range as published in the first-revised prospectus. In the auction, the lower price limit on bids is equal to the implied price of a multiple valuation discounted by 15%. Therefore, the expected offer price for the auction is equal to the lower limit on bids divided by 0.85 to account for the 15% discount.

Insider sales (in %): Secondary shares are existing shares sold by current shareholders in the IPO. On the other hand, primary shares refer to shares that are newly issued by the company in the IPO through a capital increase. The insider sales variable, in percentages, is calculated by dividing the number of secondary shares on sale by the total number of shares available for sale.

Underwriter (dummy): A dummy variable is introduced which equals 1 for the five largest underwriters and 0 for all others.[3]

Market return (in %): The market return, in percentages, is calculated by the buy-and-hold market return for a period of 60 trading days prior to the IPO date. The market return is calculated based on the JASDAQ index.

Market volatility (in %): Market volatility, in percentages, is calculated by the variance of daily market returns 20 trading days before the IPO. JASDAQ again serves as the market index.

4.3 | Linear regression analyses

The influence of the policy discontinuity on underpricing and price accuracy is analyzed by a set of multiple linear regressions. In the basic regression model, the dependent variable y_I (underpricing or absolute abnormal buy-and-hold return) is regressed on an indicator variable *Method* that equals 0 for auctions and 1 for bookbuilding and covariate vector x:

$$y_I = \alpha + b_1 (Method_I) + b_2 x_I + e$$

The coefficient of interest is b_1, which captures the influence of the price discovery method on underpricing or price accuracy after controlling for firm characteristics, IPO specific factors and market conditions. As the time window around the regulatory change from which data is considered plays an important role, we analyze the robustness using data from a wide variety of different time windows.

[3] The five largest underwriters are Nomura (590 IPOs; 28% market share), Daiwa (399 IPOs; 19% market share), Nikko (345 IPOs; 16% market share), Shinko (130 IPOs; 6% market share) and Yamaichi (103 IPOs, 5% market shares). Yamaichi operated from 1993 until bankruptcy in 1997. Shinko was formed in April 2000 as a merger of two smaller players. The market shares of Yamaichi and Shinko are diluted by years they were not operating; relative market shares in the years of operation were higher. Daiwa and Nikko changed names several times (Daiwa: Daiwa 1993-1999, Daiwa SB Capital Markets 1999-2001, Daiwa SMBC 2001-2007; Nikko: Nikko 1993-1999, Nikko Salomon Smith Barney 1999-2003, Nikko Citigroup 2003-2007).

4.4 Regression discontinuity design

A regression discontinuity design (RD or RDD; Thistlethwaite & Campbell, 1960) is an approach to estimate treatment effects in non-experimental settings.[4] The idea is that treatment is determined by an observable running variable. The excess of a known threshold (so-called cutoff point) by the running variable defines if an observation receives treatment. Ideally, the only difference between observations is that some of them got quasi-randomly assigned to receive treatment, in which case an unbiased estimator of the treatment effect can be obtained. In our case, time is the running variable and September 30, 1997, is the cutoff point. When the running variable exceeds the cutoff point, observations receive treatment in the form of being priced by bookbuilding instead of hybrid price-discriminatory auctions.

There are two types of RDD strategies (see Jacob et al., 2012). The first is the global strategy, which includes all observations, also those far away from the cutoff point. To address the possibility that unobserved factors that change over the running variable (over time, in our case) affect the outcome, higher-order polynomials of the running variable are included in the regressions. The effect of the treatment can then be estimated appropriately, even if the effect of the running variable (e.g., via unobserved factors) changes non-linearly, as long as these changes are smooth or at least continuous (discontinuous changes in unobserved factors, in particular close to the cutoff point, would be problematic). The second strategy is the local strategy, which only uses observations close to the cutoff. These observations are then analyzed with local linear regressions. Here, the effect of (unobserved) time-varying factors is usually unproblematic, because only observations close to each other in time are analyzed.

The advantage of an RDD over a regular linear regression is particularly large when there is a non-linear effect of the running variable on the outcome variable, for example if unobserved factors change over time. Regular linear regressions are problematic in such a case. RDD regressions address this by either accounting for non-linearities in the running variable with higher-order polynomials (the global strategy) or by exclusively considering observations close to the cutoff point (the local strategy).

Regression discontinuity designs improve our understanding of the effects of the regulatory change in Japan, but they are not randomized interventions and do not guarantee causality.[5] The following points may in general be problematic for a causal interpretation of the RDD estimates. A survival bias in the data may lead to biased estimates. The sample only consists of successful IPOs (those that resulted in a listing of a company at the stock exchange). If the bookbuilding method has a lower risk of failure, the true performance of the bookbuilding method relative to auctions would improve when including IPO failures. However, IPO failures in Japanese hybrid price-discriminatory auctions were rare or even non-existent (Kutsuna & Smith, 2004). There may potentially be a selection bias if the bookbuilding method attracted riskier firms, which tend to be underpriced more severely. A selection bias would only pose a serious problem if it occurred abruptly (within a short time period from the cutoff point), as it would otherwise be similar to an unobserved factor changing over time (the potential problem would further be mitigated by the fact that firm age and expected issue size are included in the regressions as control variables). In the case of Japanese IPOs, it is unlikely that the selection bias would take effect immediately after the introduction of bookbuilding as IPO mechanism, as IPOs are usually planned over longer time horizons. Furthermore, in an optimal RDD, the individual (the issuer) cannot manipulate the assignment variable. However, from the announcement that bookbuilding was to be introduced until the regulatory change entered into force, issuers could time their IPO to have their shares listed by their favored method. This means that the (in particular local RDD) estimates may be biased, but this bias should be negligible under the global approach and for regular OLS, where observations close to the cut-off are less important.

[4] RD has recently gained increasing popularity among researchers (Hausman & Rapson, 2018). A growing number of publications that investigate the influence of policy changes use RD with time as the running variable (e.g., Burger et al., 2014; Davis & Kahn, 2010). For an application to finance published in this journal, see Dai et al. (2022).

[5] Randomizing participants to treatments makes a causal interpretation straightforward. This is an advantage of experiments on IPO pricing (e.g., Weber et al., 2018; Füllbrunn et al., 2020). However, the high level of control in the laboratory comes at the expense of lower external validity. Estimates of magnitudes that are relevant for the world outside the laboratory can only rarely be obtained.

4.4.1 | Global strategy

In the regression model of the global strategy, the dependent variable y_I (underpricing or absolute abnormal return) is regressed on an indicator variable *Method* that equals 0 for auctions and 1 for bookbuilding, a vector of covariates x and a time trend $f(Time)$:

$$y_I = \alpha + b_1 (Method_I) + b_2 x_I + f(Time) + e$$

The underlying idea is that there are time-varying factors that cannot be captured through covariates in vector x. Consequently, observations far away from the cutoff point are less informative about the effect of the policy change since they are affected by time-variations (Bento et al., 2014). By specifying the relation between time and the dependent variable in a flexible way, these time-varying effects may be captured also when they are non-linear. In RD, $f(Time)$ is usually specified as a polynomial. There is no consistent approach in the literature to identify the correct specification. Therefore, we present the complete set of results for $f(Time)$ specified by first-order to sixth-order polynomials.

4.4.2 | Local strategy

The local strategy should not be seen as a substitute but rather as a complement to the global strategy (Lee & Lemieux, 2010). In the local strategy, we control for time-varying factors through a linear time trend within a local bandwidth of the policy discontinuity. The dependent variable y_I is regressed on an indicator variable *Method* that equals 0 for auctions and 1 for bookbuilding, a vector of covariates x and a linear time trend *Time*:

$$y_I = \alpha + b_1 (Method_I) + b_2 (Time) + b_3 x_I + e$$

The main challenge in the local strategy is the specification of the bandwidth. The local strategy faces a trade-off between statistical power and proximity to the cutoff point. Larger bandwidths and therefore larger sample sizes have higher statistical power, but at the same time the risk of misspecification increases (Cattaneo et al., 2020). We follow the suggestion by Imbens and Kalyanaraman (2012) to assess the sensitivity of the results on their bandwidth choice by presenting the results for a variety of bandwidths.

Local linear regressions also introduce a kernel that defines a weighting scheme (Cattaneo et al., 2020). The simplest form is a rectangular kernel which assigns to each observation the same weight, leading to standard OLS. Other kernels, such as a triangular kernel or an epanechnikov kernel, assign observations closer to the cutoff point a higher weight, as these are the most informative observations (these kernels then also reduce the risk of misspecification when the bandwidth is increased). We present the results of the local linear regression based on rectangular, triangular and epanechnikov kernels.[6]

5 | DATA

The data consist of Japanese IPOs from January 1993 to December 2007. Before 1993 the regulatory environment was not stable, with various changes in the auction method (Kaneko & Pettway, 2003). Data after 2007 is not used

[6] One can argue that the local strategy is to be preferred to the global strategy if there are enough observations around the cutoff point to accurately estimate the effect with the local strategy (Gelman & Imbens, 2019). However, as we have only a limited number of observations near the cutoff point, we present the results of both strategies.

TABLE 1 Sample description

Japanese IPOs between 01/01/1993 and 12/31/2007.		
	Growth market sample	
	Full sample	OTC
Observations	1702	1207
Auctions	481	481
Bookbuilding	1221	726
Firm Age	22.6	27.1
GP (million Yen)	2924.1	2980.9
GP (million USD)	26.6	27.4

GP stands for average gross proceeds. In auctions, gross proceeds are calculated as the number of shares sold in the auction tranche multiplied by the weighted average successful bid plus the number of shares sold in the public offer tranche multiplied by the offer price of the public offer tranche. In bookbuilding, gross proceeds are equal to the offer price multiplied by the number of shares sold. Gross proceeds in US dollars are calculated based on the USD/Yen spot rate on the IPO date. USD/Yen spot rates are obtained from Thomson Reuters Datastream. The exchange rate for the period 01/01/1993 to 08/31/1993 is kept constant at the rate of the 09/01/1993 (1 USD = 104.94 Yen) due to limited data availability before 09/01/1993. OTC is a subsample of IPOs at the Over-the-Counter market and JASDAQ.

to avoid distortions by the financial crisis which followed. There are 2175 Japanese IPOs in the complete sample.[7] The data for the bookbuilding period is publicly available from Kaneko and Pettway's Japanese IPO Database (KP-JIPO; https://www.fbc.keio.ac.jp/~kaneko/KP-JIPO/top.htm). Data for the auction period is not publicly available and was kindly provided by Kaneko and Pettway (a subsample of these data has been investigated in Kaneko & Pettway, 2003; Pettway et al., 2008). JASDAQ index prices for the period October 1992 to December 2007 are obtained from Thomson Reuters Datastream.

Regulated stock markets usually consist of separate areas. The First Sections are for large, established companies. The Second Sections are for mid-sized companies. Growth Sections or New Markets are for early-stage, high growth companies with lower listing requirements (Boutron et al., 2006). The three largest stock exchanges in Japan (Tokyo, Osaka & Nagoya) had First and Second Sections for different company types. Further, there are various regional stock exchanges (e.g., Sapporo) that mainly targeted local medium-sized companies. Before 1999, no stock exchange had a specific section for growth companies. The only stock exchange that enabled early-stage companies to go public before 1999 was the Over-the-Counter (OTC) market (converted to JASDAQ in 2004). As a reaction to growing investor demand for access to early-stage companies at the end of the 1990s, stock exchanges introduced dedicated sections for growth companies.

The data cover IPOs across all Japanese stock exchanges. However, there are no observations available for the First Sections of the Osaka Stock Exchange and the Nagoya Stock Exchange and the data miss a significant number of IPOs in the First Section of the Tokyo Stock Exchange. Consequently, First Sections are not analyzed, and 63 IPOs from the First Section of the Tokyo Stock Exchange are removed from the sample. The remaining 2112 IPOs are split into two samples. One sample consists of mid-sized companies that were listed in the Second Sections of the Tokyo Stock Exchange, the Osaka Stock Exchange and the Nagoya Stock Exchange and at regional stock exchanges ("Mature Market Sample"). The other sample consists of IPOs at growth stock exchanges ("Growth Market Sample"). Appendix A provides an overview of all Japanese stock exchanges and their classification as Growth Market, Mature

[7] The sample originally consisted of 2,180 observations. This included four privatizations which are excluded from the analysis. Further, the information about the IPO of Club IT (SEC: 4347) is inconsistent: The upper limit of the filing range is unreasonably high at 20,020,219 Japanese Yen; we assume that the upper limit was accidentally overwritten with a date (2002/02/19). This IPO is therefore removed from the sample. Furthermore, the first-day closing share price of Infocom (SEC: 4348) of -99.2% is implausible and inconsistent with Thomson Reuters Datastream; the value was therefore adjusted based on the data from Thomson Reuters Datastream.

Market or Excluded Market.[8] In this article, we only analyze the Growth Market Sample, which has a much larger number of observations. The findings when analyzing the Mature Market Sample are similar; the analyses of that sample can be found in the earlier and more extensive working paper version of this article (Lehmann & Weber, 2021).

Table 1 describes the Growth Market Sample. Firms listed at the OTC stock market are on average older than the others. This is partially driven by the fact that the OTC market is the only stock exchange in the Growth Market Sample that was operating during the auction period. The Growth Market Sample consists of 1702 observations. Most observations in the Growth Market Sample are IPOs at the JASDAQ/OTC market. Therefore, a subsample that only includes JASDAQ/OTC listings is also analyzed ("OTC Subsample").

6 | RESULTS ON UNDERPRICING

The analysis of underpricing is split into three sections. First, descriptive statistics are provided. Afterwards, the results of the multiple linear regression models are discussed. Finally, the findings of the regression discontinuity designs are presented.

6.1 | Descriptive statistics (underpricing)

Underpricing in Japan fluctuated significantly over time, as shown in Table 2. While underpricing between 1993 and 1998 was rather low, initial returns strongly increased in 1999. Afterwards, underpricing decreased again (to levels higher than before 1998) and peaked again in the year 2005.

The development of underpricing over time is shown in Figure 3 (the dot-com bubble 1999/2000 is the shaded area). One can see that underpricing in the auction period is on average lower and less volatile than in the bookbuilding period.

The bookbuilding and auction subsamples are described in Table 3. The bookbuilding period covers a longer time period and thus contains more observations. The largest five underwriters coordinated 80.87% of all IPOs in the auction period and 66.74% in the bookbuilding period. IPO auctions are on average underpriced by 7.42%, while bookbuilt IPOs are on average underpriced by 72.77%. According to a simple t-test, auctions have significantly lower initial returns ($p = 0.000$). However, firms going public by bookbuilding are on average younger ($p = 0.000$), expected issue sizes are lower ($p = 0.000$), fewer secondary shares are on sale ($p = 0.001$), and market returns ($p = 0.002$) and market volatility ($p = 0.000$) before the IPO were higher.

6.2 | Linear regression analyses (underpricing)

We analyze the sample with a Method dummy for the IPO method. Model 1 to Model 3 in Table 4 analyze the full Growth Market Sample and Model 4 to Model 6 in Table 4 are based on the OTC Subsample. A point of concern is the influence of the dot-com bubble period (April 1999–July 2000) on the results. While Model 1 and Model 4 do not control for this period, Model 2 and Model 5 introduce a dummy variable. Model 3 and Model 6 exclude dot-com bubble IPOs from the analysis.

The Method coefficient estimate is statistically significant at the 0.1%-level in all six models with values between 35.83 and 37.51 (percentage points) for the Growth Market Sample (29.07–33.41 for the OTC Subsample). Underpric-

[8] For the price accuracy analysis, the monthly stock price data for each IPO firm is required. As an identifier for each firm, only the local Japanese Security Code is available. Through matching and verification, the ISIN number for 1,784 out of 2,112 IPOs could be identified and validated. The Growth Market Sample for the analysis of price accuracy consists of 1,448 observations and the Mature Market Sample of 336 observations. Based on the ISIN number, stock price data for each IPO firm and index prices for the benchmark indices are obtained from Thomson Reuters Datastream.

TABLE 2 Underpricing by year

Underpricing between 01/01/1993 and 12/31/2007 (Growth Market Sample)				
	Full sample		OTC	
Year	Observations	Underpricing	Observations	Underpricing
1993	54	8.9	54	8.9
1994	106	7.6	106	7.6
1995	137	8.7	137	8.7
1996	110	9.4	110	9.4
1997[a]	74	0.8	74	0.8
1997[b]	29	10.2	29	10.2
1998	62	23.8	62	23.8
1999	76	135.6	73	134.8
2000	161	19.8	97	21.2
2001	149	49.8	97	34.4
2002	99	35.3	68	29.0
2003	101	58.8	62	37.2
2004	149	112.3	71	94.2
2005	138	148.7	65	104.9
2006	151	89.6	56	58.6
2007	106	56.1	46	42.1

Underpricing stands for average underpricing (in %). OTC is a subsample of IPOs at the Over-the-Counter market (converted to JASDAQ in 2004). Note that there is an overlap between the two methods because the last auctioned IPO took place seven days after the first book-built IPO.

[a]Auction period (January 1 – October 7).

[b]Bookbuilding period (September 30 – December 31).

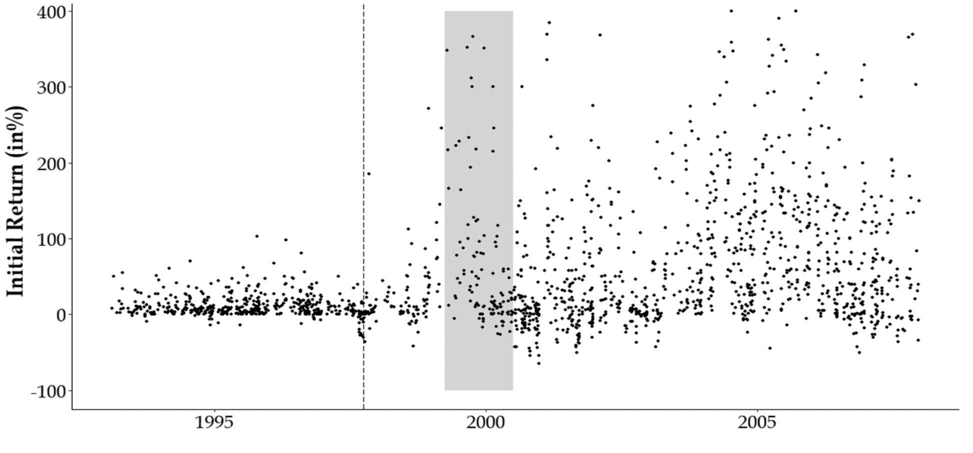

FIGURE 3 Underpricing over time (underpricing between 01/01/1993 and 12/31/2007, Growth Market Sample). Each point represents one IPO of 1702 IPOs in the growth market sample. 27 book-built IPOs exhibited an initial return that exceeded 400% and are therefore not shown in the graph. The dashed vertical line indicates the date of the policy change (09/30/1997). Observations to the left are auctions and observations to the right are bookbuildings (except for one auctioned IPO on October 7, 1997 with an initial return of –0.39%). The shaded box highlights the dot-com bubble period (04/01/1999 to 06/30/2000)

TABLE 3 Underpricing – Descriptive statistics

Japanese IPOs between 01/01/1993 and 12/31/2007 (Growth market sample)				
	Auction subsample		Bookbuilding subsample	
Observations	481		1221	
Top 5 underwriter	389		815	
Bubble period	0		121	
	Average	Median	Average	Median
Underpricing	7.42%	3.97%	72.77%	33.96%
Firm age	30.34	30.07	19.61	15.97
log (Firm Age)	3.30	3.40	2.65	2.77
Expected issue size	2767 m	1864 m	2495 m	1015 m
log (Exp. issue size)	21.38	21.35	20.84	20.74
Insider sales	39.37%	44.59%	35.62%	37.50%
Market return	−1.85%	−3.52%	0.54%	−1.63%
Market volatility	0.0065%	0.0043%	0.0205%	0.0095%

Top 5 Underwriter refers to the number of IPOs underwritten by one of the five largest investment banks. Bubble Period refers to the number of IPOs between 04/01/1999 and 06/30/2000. See Section 4.2.3 for a detailed description of each covariate. The currency of the expected issue size is Japanese Yen.

ing is thus significantly higher for bookbuilding than for hybrid price-discriminatory auctions after controlling for firm characteristics, IPO specific factors and market conditions. This confirms the findings of Kaneko and Pettway (2003).

The results in all six models also indicate that older firms exhibit lower initial returns. This can be attributed to lower ex-ante price uncertainty and is consistent with Arikawa and Imad'eddine (2010), Kaneko and Pettway (2003), Kirkulak (2004), Kirkulak (2008) and Kirkulak and Davis (2005). The market return coefficient is statistically significant at the 0.1%-level in all six models. This indicates that market returns before the IPO are not fully incorporated in the offer price. A one percentage point higher market return before the IPO increases underpricing by about 2 percentage points based on the results of Model 1 to Model 3. Thus, IPOs in "hot" markets are associated with higher underpricing. These results are consistent with Lowry and Schwert (2004) and Loughran and Ritter (2002), who argue that public information such as pre-IPO market returns are not fully incorporated into the offer price. The expected issue size is negatively related to underpricing and the coefficients are significant at the 0.1%-level (except for Models 4 and 5).

This confirms the results of Kaneko and Pettway (2003) and Arikawa and Imad'eddine (2010). Kirkulak (2008) and Kirkulak and Davis (2005) suggest that higher percentages of secondary shares on sale in the IPO lower underpricing. The negative Insider Sales coefficients in Table 4 provide supporting evidence for this. Finally, all models find no statistically significant relation between underpricing and underwriter reputation as well as between underpricing and market volatility. This is consistent with Kaneko and Pettway (2003).

Ritter and Welch (2002) argue that underpricing is non-stationary and subject to substantial time-variations, which makes the results of empirical research sensitive to the choice of the sample period. The sensitivity of the results in Table 4 to the sample period is investigated in Figure 4. The graph plots the relation between the Method coefficient estimate and the bandwidth, which specifies the data that is analyzed in the regression. The first data point in Figure 4 plots the Method coefficient estimate for a bandwidth of 270 days. This means that only observations from 270 days before the policy change to 270 days after the policy change are analyzed. The last data point (bandwidth of 3740) is based on the full Growth Market Sample and the Method coefficient estimate is therefore equal to the estimate reported in Table 4. The solid (red) line is based on the specification of Model 1 in Table 4. The dashed (blue) line in the

TABLE 4 Underpricing – Regression results (full sample)

Japanese IPOs between 01/01/1993 and 12/31/2007 (Growth Market Sample)						
Data	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Stock exchange	All	All	All	OTC	OTC	OTC
Bubble period	-	Dummy	Data exc.	-	Dummy	Data exc.
Results						
Intercept	359.60	357.06	409.09	137.14	148.24	186.18
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.001)***	*(0.000)****	*(0.000)****
Method	37.28	37.51	35.83	33.41	32.16	29.07
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
Log age	−27.53	−27.46	−25.03	−22.96	−23.07	−16.00
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
Log (Exp. issue size)	−11.63	−11.53	−14.56	−1.69	−2.17	−5.48
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.399)*	*(0.252)*	*(0.001)****
Insider sales	−0.32	−0.32	−0.23	−0.41	−0.40	−0.24
	*(0.010)***	*(0.009)***	*(0.050)*	*(0.001)***	*(0.001)***	*(0.016)**
Market return	2.01	2.04	1.96	1.74	1.57	1.46
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
Market volatility	−108.40	−85.92	155.48	−21.12	−125.49	402.62
	(0.056)	*(0.313)*	*(0.411)*	*(0.704)*	*(0.182)*	*(0.139)*
Underwriter	5.58	5.72	5.31	2.02	1.51	1.21
	(0.256)	*(0.246)*	*(0.274)*	*(0.673)*	*(0.754)*	*(0.767)*
Bubble		−5.07			22.85	
		(0.764)			*(0.254)*	
Observations	1702	1702	1581	1207	1207	1104
Adj. R-squared	0.232	0.232	0.238	0.241	0.243	0.227

In all six OLS regressions, the dependent variable is underpricing. p-values shown in parenthesis are based on heteroscedasticity-consistent standard errors. See Section 4.2.3 for a detailed description of each covariate. ExpIS abbreviates the expected issue size. In Model 1 to Model 3 the Growth Market Sample is analyzed. In Model 4 to Model 6 the OTC Subsample is investigated. Model 1 and Model 4 do not account for the dot-com bubble 1999/2000. Model 2 and Model 5 introduce a dot-com bubble 1999/2000 dummy variable that equals 1 for observations between 04/01/1999 and 06/30/2000. Model 3 and Model 6 exclude observations between 04/01/1999 and 06/30/2000 from the analysis.
Significance levels are as follows:
* = 0.05.
** = 0.01.
*** = 0.001

upper panel includes an additional bubble dummy (Model 2 in Table 4). Further, the dashed (blue) line in the lower panel excludes observations during the dot-com bubble 1999/2000 (Model 3 in Table 4). The graphs include 95%-confidence intervals.

The highest Method coefficient for pre-bubble bandwidths of 270 to 548 is estimated at 11.0. High underpricing during the dot-com bubble 1999/2000 seems to significantly increase the Method coefficient estimate (solid red line), when these data are included. The highest estimate of the Method coefficient for the dot-com bubble bandwidths of 548 to 1040 (grey box) is estimated at 29.2. When controlling for or excluding the dot-com bubble, the estimates of the Method coefficient for this period represented by the two dashed (blue) lines remain below 16.0. The development of

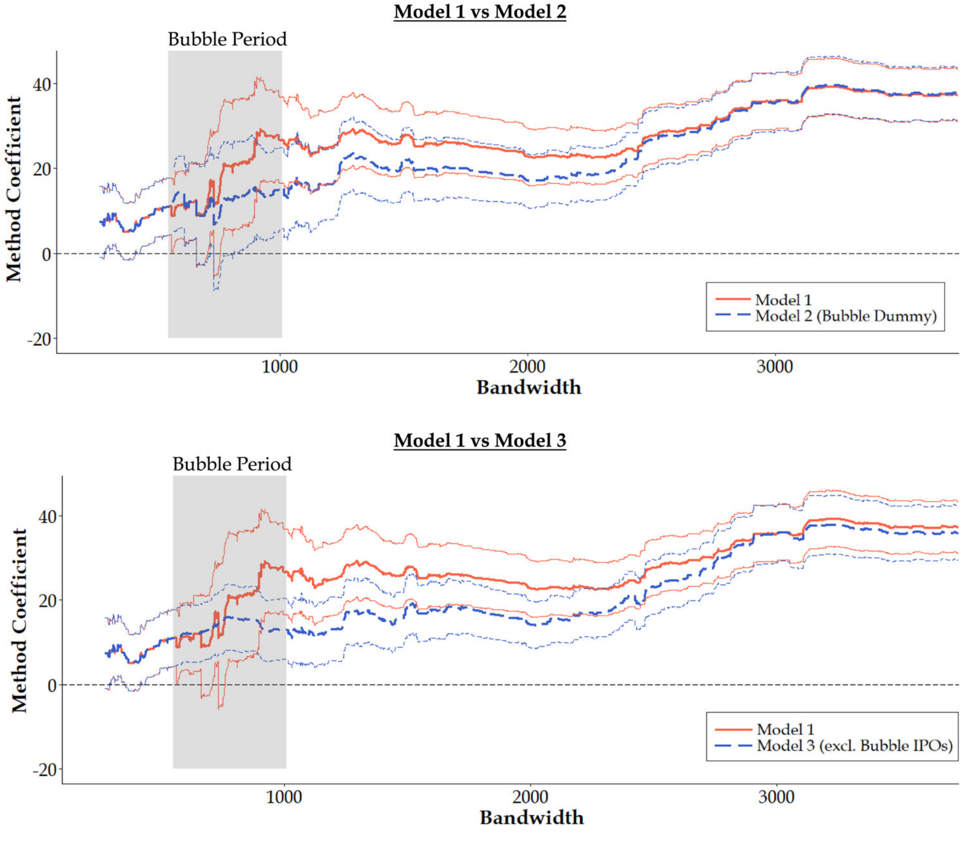

FIGURE 4 Method coefficient and bandwidth, multiple linear regression (method coefficient sensitivity and dot-com Bubble 1999/2000, Growth Market Sample). This figure presents the estimate of the Method coefficient for 10410 OLS regressions. In all regressions, the dependent variable is underpricing. The solid (red) line is based on the regression equation of Model 1 in Table 4. The dashed (blue) lines in the upper and lower panels account for the dot-com bubble 1999/2000 and are based on the regression equations of Models 2 and 3 in Table 4, respectively. The shaded box highlights the bandwidths that cover the dot-com bubble period (04/01/1999 to 06/30/2000). Furthermore, 95%-confidence intervals are presented. Bandwidth specifies the data that is included. Note that even though the dashed (blue) line in the lower panel excludes dot-com bubble 1999/2000 observations from the analysis, the Method coefficient changes during this period because the number of observations from the auction period is increasing with a growing bandwidth

the Method coefficient in the post-bubble period is particularly interesting. By increasing the bandwidth, the Method coefficient estimates increase for all three model specifications.

6.3 | Regression discontinuity designs (underpricing)

The results thus far confirm the findings of Kaneko and Pettway (2003) and increase their robustness by investigating data from different time periods and varying subsamples and model specifications. However, Figure 4 reveals that the results might be sensitive to the choice of the sample period. In the following, we use RDDs to disentangle the influence of the policy change on underpricing from other unobserved time-varying factors. As discussed in Section 4.4, there are two complementary RD strategies, the global and the local strategy.

TABLE 5 Underpricing – RD global strategy results

Japanese IPOs between 01/01/1993 and 12/31/2007 (Growth Market Sample)				
Data	Model 1	Model 2	Model 3	Model 4
Stock exchange	All	All	OTC	OTC
Bubble	-	Dummy	-	Dummy
Observations	1702	1702	1207	1207
Method coefficient estimates				
Linear time trend	−10.669	−15.59	7.09	−2.25
	(0.123)	(0.011)*	(0.296)	(0.668)
Quadratic time trend	−6.73	−10.49	7.53	2.21
	(0.270)	(0.038)*	(0.159)	(0.615)
Cubic time trend	−12.18	−20.49	8.88	0.05
	(0.117)	(0.002)**	(0.210)	(0.993)
Fourth-order polynomial time trend	42.05	34.43	34.81	28.96
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Fifth-order polynomial time trend	28.17	23.40	28.77	23.90
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Sixth-order polynomial time trend	25.32	23.53	17.62	18.08
	(0.001)***	(0.001)**	(0.005)**	(0.003)**

The table presents the results of the Method coefficient for 24 OLS regressions with underpricing as the dependent variable. In all regressions, the covariates introduced in Section 4.2.3 are included in the regression equation. In Model 2 and Model 4 a bubble dummy is included in the regression equation that equals 1 for observations between 04/01/1999 and 06/30/2000. In Model 3 and Model 4 the OTC Subsample is investigated. For each model, six OLS regressions are conducted with different specifications of f(Time). p-values shown in parenthesis are based on heteroscedasticity-consistent standard errors. No model excludes IPOs during the dot-com bubble 1999/2000, because the underlying idea of the global strategy is that every single observation is included in the analysis and that the time trend specification captures time-variations.
Significance levels are as follows:
*= 0.05.
** = 0.01.
*** = 0.001

6.3.1 | RD global strategy (underpricing)

The global strategy of the regression discontinuity design accounts for unobserved time-varying effects by a polynomial time trend. Table 5 presents the Method coefficient estimates for regressions with first- to sixth-order polynomial time trends. Model 1 and Model 2 investigate the Growth Market Sample while Model 3 and Model 4 analyze the OTC Subsample. Further, Model 2 and Model 4 introduce a dot-com bubble dummy variable.

The Method coefficient estimates for linear, quadratic and cubic time trends in Table 5 are partly positive, partly negative and mainly insignificant. Higher-order polynomials are more flexible and can more easily capture non-linear time-varying effects. Fourth- to sixth-order polynomial time trends yield statistically significant results across all four models and the Method coefficient estimates are more consistent.

The latter results indicate that underpricing for bookbuilding is between 23.40 and 42.05 percentage points higher than for auctions (OTC Subsample: 17.62 to 34.81 percentage points). The results for a fourth-order polynomial time trend are in a similar range to the Method coefficients reported in Table 4, while the Method coefficient estimates for fifth- and sixth-order polynomial time trends tend to be lower. Even though there are variations in the Method coefficient estimates in Table 5, the results overall provide evidence that underpricing is significantly higher for bookbuilding than for auctions.

TABLE 6 Underpricing – RD local strategy results

Japanese IPOs between 04/09/1996 and 03/10/1999 (Growth market sample)				
Kernel		Model 1 Rectangular	Model 2 Triangular	Model 3 Epanechnikov
Bandwidth	Observations	Method coefficient	Method coefficient	Method coefficient
270 days	119	12.81	8.24	9.79
		(0.088)	*(0.270)*	*(0.181)*
360 days	177	14.58	10.81	12.40
		*(0.013)**	*(0.124)*	*(0.071)*
450 days	242	8.66	11.86	12.70
		(0.140)	*(0.041)**	*(0.020)**
540 days	270	3.89	10.37	9.92
		(0.544)	*(0.055)*	*(0.059)*

The table presents the results of the Method coefficient for 12 regressions with underpricing as the dependent variable. In all regressions, the covariates introduced in Section 4.2.3 are included in the regression equation. p-values shown in parenthesis are based on heteroscedasticity-consistent standard errors. Bandwidth specifies the data that is included. In Model 1 a rectangular kernel is used. Model 2 is based on a triangular kernel and Model 3 is based on an epanechnikov kernel.
Significance levels are as follows:
* = 0.05.
** = 0.01.
*** = 0.001

6.3.2 | RD local strategy (underpricing)

The estimates of the Method coefficient for the local linear regression with bandwidths between 270 days and 540 days are presented in Table 6. The lower limit of 270 days is chosen because the number of observations for smaller bandwidths is too low to have any explanatory power. The upper limit is defined at 540 days to exclude the dot-com bubble 1999/2000. Model 1 uses a rectangular kernel, Model 2 a triangular kernel, and Model 3 an epanechnikov kernel. The results for the Growth Market Sample and the OTC Subsample are the same because the OTC market was the only growth stock exchange operating before the dot-com bubble period 1999/2000.

The results in Table 6 indicate that bookbuilding leads to higher underpricing than auctions. Almost all Method coefficients indicate that underpricing for bookbuilding is around ten percentage points higher than for auctions. These results are confirmed and graphically illustrated in Figure 5. The three types (and colors) of lines show the results based on three different kernels. The corresponding 95% confidence intervals are also presented. A triangular kernel and an epanechnikov kernel assign observations closer to the cutoff point a higher weight. When extending the bandwidth, the weight of additional observations is rather low, which leads to a smooth development of the Method coefficient estimate. In contrast, with a rectangular kernel, all observations have the same weight and additional observations can therefore lead to less smooth changes in the estimate of the Method coefficient when increasing the bandwidth.

Note that the majority of Method coefficients are statistically insignificant for the lower bandwidths, while the majority are at least marginally significant for the higher bandwidths (the level of significance is in general somewhat lower than for the regressions reported in Table 4). This is not surprising, because the numbers of observations are considerably lower in the local RDD regressions, especially for the lower bandwidths. The numbers of observations are between 119 and 270 in the RDD regressions reported in Table 6, depending on the bandwidth (as compared to between 1104 and 1702 in the regressions in Table 4). That the estimated method coefficient is of similar magnitude for most bandwidths suggests that the missing significance for the RDD regressions with lower bandwidth is just due to the lower number of observations.

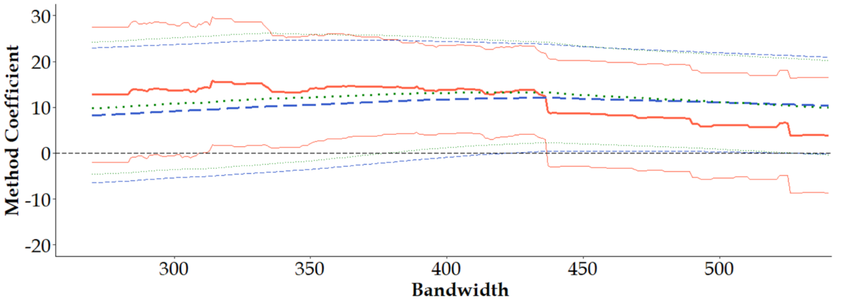

FIGURE 5 Method coefficient and bandwidth, RD local strategy (bandwidth sensitivity of the Method coefficient, Growth Market Sample). The figure presents the Method coefficient estimates of 1620 regressions. In all regressions, the dependent variable is underpricing, and the covariates introduced in Section 4.2.3 together with a linear time trend are included in the regression equation. The solid (red) line presents the results for a rectangular kernel. The dashed (blue) line stands for a regression based on a triangular kernel and the dotted (green) line presents the result for an epanechnikov kernel. The corresponding 95% confidence intervals are also shown. Bandwidth specifies the data that is included

In conclusion, the local linear regressions also indicate that initial returns are higher for bookbuilding than for auctions. The results suggest that by evaluating only observations close to the policy discontinuity, the Method coefficient is estimated to be lower than in the multiple linear regression analysis in Table 4. This confirms the pattern observed in Figure 4. Underpricing (with bookbuilding) became particularly large with the dot-com bubble, and it remained at very high levels after the dot-com bubble. However, underpricing with bookbuilding was already higher before the dot-com bubble than with auctions, by about ten percentage points.

7 | RESULTS ON PRICE ACCURACY

We first provide descriptive statistics and then the results of the linear regression analyses. This is followed by the findings from the regression discontinuity designs. The results are robust to a variety of changes, such as using absolute abnormal returns over 36 months instead of over 12 months, using algebraic abnormal returns instead of absolute abnormal returns, or using the Topix index as benchmark instead of the JASDAQ. These robustness checks can be found in the earlier and longer working paper version of this article (Lehmann & Weber, 2021).

7.1 | Descriptive statistics (price accuracy)

Descriptive statistics are provided in Table 7. Auctioned IPOs deviate on average from the JASDAQ benchmark by 27.33 percentage points (considering 12-month absolute abnormal returns). For bookbuilding, the absolute abnormal buy-and-hold return is on average 66.48 percent based on the JASDAQ benchmark. The median values are lower for both price discovery methods, which indicates that some outliers strongly underperform or outperform the benchmark (as the price accuracy measure is based on absolute values, high values can indicate underperformance or outperformance). However, the median absolute abnormal buy-and-hold returns are still significantly higher for bookbuilding than for auctions.

7.2 | Linear regression analyses (price accuracy)

The results of the regression analyses are presented in Table 8. The Method coefficients are positive and statistically significant at the 0.1% level in all six models with values between 34.04 and 35.25 for the full Growth Market Sample

TABLE 7 Price accuracy – Descriptive statistics

Japanese IPOs between 01/01/1993 and 12/31/2007 (Growth market sample)				
	Auction subsample		Bookbuilding subsample	
Observations	466		982	
Top 5 underwriter	379		666	
Bubble period	0		106	
Dependent variable	**Average**	**Median**	**Average**	**Median**
Abs. AR 12 m JASDAQ	27.33%	22.48%	66.48%	41.14%
Independent variables				
Firm age	30.33	30.15	21.48	18.47
log (Firm age)	3.31	3.41	2.76	2.92
Expected issue size	2775 m	1856 m	2737 m	1080 m
log (Exp. issue size)	21.38	21.34	20.90	20.80
Insider sales	39.33%	44.67%	36.94%	39.39%
Market return	−2.11%	−3.69%	−0.15%	−2.77%
Market volatility	0.0065%	0.0043%	0.0214%	0.0103%

Top 5 Underwriter refers to the number of IPOs that were underwritten by one of the five largest investment banks. Bubble Period refers to the number of IPOs between 04/01/1999 and 06/30/2000. Abs. AR 12m stands for absolute abnormal buy-and-hold return over a 12-month post-listing period. The calculation of absolute abnormal buy-and-hold returns is described in Section 4.2.2. See Section 4.2.3 for a detailed description of each covariate. The currency of the expected issue size is Japanese Yen.

(39.25–40.02 for the OTC Subsample). In other words, the absolute deviation of the 12-month buy-and-hold return from the benchmark return is on average between 34.04 and 35.25 percentage points higher for bookbuilding than for auctions in the full Growth Market Sample. Thus, the price accuracy of auctioned IPOs is higher.

7.3 | Regression discontinuity designs (price accuracy)

We again present both complementary strategies of the regression discontinuity design.

7.3.1 | RD global strategy (price accuracy)

The Method coefficients of the global RDD are presented in Table 9. Model 1 analyzes the full Growth Market Sample. The results indicate that the price accuracy for auctions is significantly higher than for bookbuilding, confirming the results of the multiple linear regression analysis. The results show little sensitivity to the order of the polynomial time trend. Further, the Method coefficient estimates in Table 9 are higher than the estimates of the regression analysis in Table 8. The regression results in Model 2 are based on the OTC Subsample and similarly indicate that price accuracy for auctions is significantly higher than for bookbuilding.

7.3.2 | RD local strategy (price accuracy)

The results of the local strategy of the regression discontinuity design are presented in Table 10. The models use JASDAQ as benchmark. The models use again a rectangular, triangular and epanechnikov kernel. The results indicate that

TABLE 8 Price accuracy – Regression results (JASDAQ benchmark)

Japanese IPOs between 01/01/1993 and 12/31/2007 (Growth Market Sample)						
Data	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Data	All	All	All	OTC	OTC	OTC
Bubble period	-	Dummy	Data exc.	-	Dummy	Data exc.
Benchmark	JASDAQ	JASDAQ	JASDAQ	JASDAQ	JASDAQ	JASDAQ
Period	12 months	12 months	12 months	12 months	12 months	12 months
Results						
Intercept	213.95	211.89	218.02	227.01	224.47	221.04
	*(0.010)***	*(0.010)***	*(0.011)**	*(0.044)**	*(0.044)**	*(0.060)*
Method	34.04	34.31	35.25	39.25	39.54	40.02
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
Log age	−11.70	−11.66	−11.78	−22.11	−22.11	−23.21
	*(0.031)**	*(0.031)**	*(0.037)**	*(0.026)**	*(0.026)**	*(0.029)**
Log (Exp. issue size)	−7.82	−7.74	−8.03	−6.79	−6.67	−6.41
	*(0.026)**	*(0.027)**	*(0.028)**	*(0.122)*	*(0.124)*	*(0.161)*
Insider sales	0.21	0.20	0.23	0.20	0.20	0.24
	(0.150)	*(0.152)*	*(0.116)*	*(0.245)*	*(0.246)*	*(0.187)*
Market return	0.09	0.14	0.08	−0.12	−0.07	−0.15
	(0.545)	*(0.442)*	*(0.704)*	*(0.482)*	*(0.736)*	*(0.520)*
Market volatility	−181.56	−149.53	−301.59	−189.29	−163.66	−263.13
	*(0.000)****	*(0.005)***	*(0.196)*	*(0.001)***	*(0.004)***	*(0.390)*
Underwriter	15.49	15.65	15.94	14.32	14.43	14.76
	*(0.028)**	*(0.028)**	*(0.035)**	*(0.068)*	*(0.067)*	*(0.080)*
Bubble		−7.10			−5.74	
		(0.414)			*(0.576)*	
Observations	1448	1448	1342	1147	1147	1049
Adj. R-squa.	0.030	0.029	0.029	0.039	0.038	0.039

In all six OLS regressions, the dependent variable is the absolute abnormal buy-and-hold return over a 12-month post-listing period based on the JASDAQ index benchmark. Model 1 to Model 3 are based on the Growth Market Sample and Model 4 to Model 6 are based on the OTC Subsample. While Model 1 and Model 4 do not control for the dot-com bubble 1999/2000, Model 2 and Model 5 introduce a bubble dummy variable. Further, Model 3 to Model 6 exclude observations between 04/01/1999 and 06/30/2000 from the analysis. p-values shown in parenthesis are based on heteroscedasticity-consistent standard errors. See Section 4.2.3 for a description of each covariate.
Significance levels are as follows:
* = 0.05.
** = 0.01.
*** = 0.001

the price accuracy is higher for auctions than for bookbuilding with Method coefficients between 12.72 and 92.96. The results are consistent across different kernel specifications. The results for the Growth Market Sample and the OTC Subsample are again the same since the OTC market was the only growth stock exchange operating before the dot-com bubble. The coefficients are insignificant for the low bandwidths, which have low numbers of observations (here, in contrast to the underpricing analysis, the coefficient estimates of the lower bandwidths are also lower than the estimates for higher bandwidths).

TABLE 9 Price Accuracy – RD Global Strategy Results

Japanese IPOs between 01/01/1993 and 12/31/2007 (Growth Market Sample)		
Data	**Model 1**	**Model 2**
Stock exchange	All	OTC
Bubble	Dummy	Dummy
Benchmark	JASDAQ	JASDAQ
Period	12 months	12 months
Observations	1448	1147
Method coefficient estimates		
Linear time trend	109.78	124.29
	*(0.000)******	*(0.000)******
Quadratic time trend	110.17	120.40
	*(0.000)******	*(0.000)******
Cubic time trend	123.20	138.06
	*(0.001)******	*(0.001)******
Fourth-order polynomial time trend	147.83	151.22
	*(0.001)****	*(0.001)******
Fifth-order polynomial time trend	142.87	146.21
	*(0.001)******	*(0.001)******
Sixth-order polynomial time trend	164.30	159.52
	*(0.000)******	*(0.000)******

The table presents the Method coefficient estimates of 12 OLS regressions with absolute abnormal buy-and-hold returns over a 12-month post-listing period as the dependent variable. Model 1 is based on the Growth Market Sample and Model 2 on the OTC Subsample. In all regressions, the covariates introduced in Section 4.2.3 and a bubble dummy are included in the regression equation. The models are based on the JASDAQ index benchmark. For each model, six OLS regressions are conducted with different specifications of f(Time). p-values shown in parenthesis are based on heteroscedasticity-consistent standard errors.
Significance levels are as follows:
* = 0.05.
** = 0.01.
*** = 0.001

8 | DISCUSSION

There is robust evidence that bookbuilding leads to higher initial returns than hybrid price-discriminatory auctions. The influence of the policy change on underpricing is economically relevant. Estimated effects are that bookbuilding leads to underpricing that is between 10 and 40 percentage points higher than that of auctioned IPOs. Furthermore, stocks are priced less accurately in the aftermarket for bookbuilding than for hybrid price-discriminatory auctions. This stands in contrast to theoretical arguments stating that higher underpricing in bookbuilding is a consequence of higher information production by investors.

Our results indicate that the interests of the issuer and the underwriter may not be fully aligned. Underpricing in bookbuilding thus seems to be at least partially driven by principal-agent conflicts. From this perspective, the regulation that was in place until 1997 was beneficial.

One may wonder why issuers in Japan switched to bookbuilding after the introduction of that method and never again used auctions to price and allocate IPOs (after one single last IPO auction, early in the month after bookbuilding had become possible). One potential explanation, which would be in line with the principal-agent conflict between

TABLE 10 Price accuracy – RD local strategy results

Japanese IPOs between 04/09/1996 and 03/10/1999 (Growth Market Sample)				
		Model 1	**Model 2**	**Model 3**
Benchmark		JASDAQ	JASDAQ	JASDAQ
Period		12 months	12 months	12 months
Kernel	Rectangular	Triangular	Epanechnikov	
Bandwidth	**Observations**	**Method coefficient**	**Method coefficient**	**Method coefficient**
270 days	119	20.80	12.72	16.09
		(0.167)	*(0.413)*	*(0.291)*
360 days	175	58.50	19.90	26.65
		*(0.015)**	*(0.247)*	*(0.161)*
450 days	239	86.27	46.45	57.24
		*(0.020)**	*(0.016)**	*(0.014)**
540 days	261	92.96	61.24	72.10
		*(0.020)**	*(0.013)**	*(0.014)**

The table presents the Method coefficient estimates of 12 regressions with absolute abnormal buy-and-hold returns over a 12-month post-listing period as the dependent variable. In all regressions, the covariates introduced in Section 4.2.3 and a linear time trend are included in the regression equation. The benchmark is the JASDAQ index. In Model 1 a rectangular kernel is used. Model 2 is based on a triangular kernel and Model 3 is based on an epanechnikov kernel. p-values shown in parenthesis are based on heteroscedasticity-consistent standard errors. Bandwidth specifies the data that is included.
Significance levels are as follows:
* = 0.05.
** = 0.01.
*** = 0.001

issuers and underwriters, is that it is not issuers or investors but underwriters who favor bookbuilding. The underwriter is only a facilitator of the price discovery process in the auction method but has significant pricing and share allocation discretion in bookbuilding. Arikawa and Imad'eddine (2010) show that the Japanese IPO market was an oligopoly with the top three underwriters having a market share of about 70% directly after the regulatory change in 1997. An IPO is for most firms a one-time event and the decision makers rely considerably on the recommendations of the underwriter. The dominant underwriters may have seen it in their interest to establish bookbuilding as the method of choice as soon as it was introduced in Japan.

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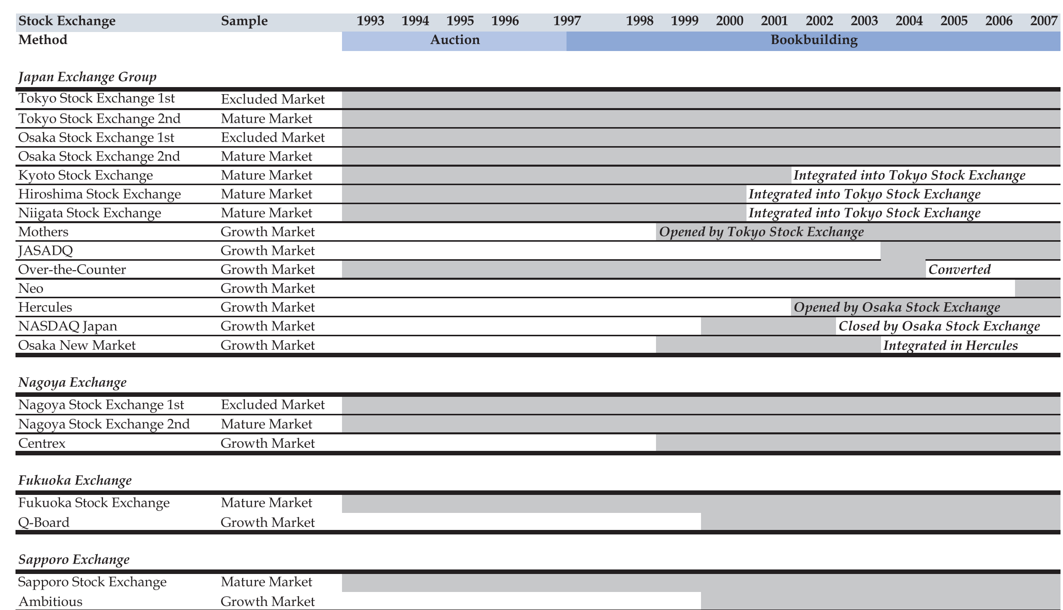
APPENDIX A: JAPANESE STOCK EXCHANGES



Gray shading indicates years of operation.

APPENDIX B: COVARIATE FORMULAS

Covariate formulas

Including Offer Price and Expected Offer Price Formulas

This table provides the formulas for the calculation of each covariate, the offer price and the expected offer price. All calculations are based on the local currency (Japanese Yen).

	Offer Price and Expected Offer Price Formulas	
	Auction Subsample	**Bookbuilding Subsample**
Expected Offer Price (EOP)	$\frac{\textit{Lower Limit on Bids}}{0.85}$	*Average of the Filing Range*
Offer Price (OP)	$\%$ *of Auctioned Shares* $*$ *WESB* $+$ $\%$ *of POT Shares* $*$ *Price POT*	*Price defined by Underwriter*

Note: % of Auctioned Shares = Percentage of Shares Sold in the Auction Tranche; WESB = Weighted Average of Successful Bids; % of POT Shares = Percentage of Shares Sold in the Public Offer Tranche; POT = Public Offer Tranche

	Covariate Formulas
Firm Age (log)	$\log(\textit{IPO date} - \textit{Founding date})$
Expected Issue Size (log)	$\log(\textit{EOP} * \textit{Total Number of Shares on Sale})$
Insider Sales (in %)	$\frac{\textit{Number of Secondary Shares on Sale}}{\textit{Total Number of Shares on Sale}} * 100$
Underwriter (Dummy)	*Top 5 Underwriters*
Market Return (in %)	$\frac{\textit{Index } CP_{\textit{IPO date}} - \textit{Index } CP_{\textit{IPO date}-60 \textit{ trading days}}}{\textit{Index } CP_{\textit{IPO date}-60 \textit{ trading days}}} * 100$
Market Volatility (in %)	*Variance of Daily Index Prices* 20 *Trading Days before IPO* $*$ 100