Nepotism in IPOs: consequences for issuers and investors

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September 2020

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Keywords: Underpricing, IPOs, Affiliated funds, Conflicts of interest, RDD

JEL Classifications: G23, G24, G39

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Nepotism in IPOs: Consequences for Issuers and Investors

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Nepotism in IPOs: consequences for issuers and investors[1]

François Degeorge[2] and Giuseppe Pratobevera[3]

Abstract

Potential conflicts of interest arise when IPO underwriters allocate IPO shares to their affiliated funds. We hypothesize that such nepotism incentives affect IPO pricing. Using a novel hand-collected dataset, we find support for this hypothesis in a regression discontinuity design (RDD): a one percentage point increase in affiliated allocations increases underpricing by 5.4 percentage points. Our evidence suggests that nepotism has real monetary costs for IPO issuers. We also use our dataset to revisit a milder version of nepotism analyzed in prior studies, and we find much clearer support for it than prior work: we find a strong positive association between IPO underpricing and affiliated allocations, which strengthens when nepotism incentives are stronger.

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1. Introduction and motivation

We identify a hitherto unexplored conflict of interest faced by investment banks taking companies public and we document its consequences for IPO pricing. Investment banks that are part of a banking group with an asset management arm have an incentive to underprice IPOs when they expect that funds affiliated to the same bank will receive IPO shares. We examine this conflict of interest empirically. Our evidence supports the view that this conflict of interest induces banks to underprice IPOs by economically significant amounts.

In the traditional IPO process the underwriting banks have a primary say over the IPO offering price, as well as most of the power on initial share allocation. When an IPO underwriter is affiliated with a fund manager, three potential conflicts of interest arise:

- The underwriter may allocate shares in overpriced ("cold") IPOs to its affiliated funds in order to ensure the completion of the issue. Ritter and Zhang (2007) refer to this conflict of interest as the "dumping ground" hypothesis.
- The underwriter may allocate shares in underpriced ("hot") IPOs to its affiliated funds in order to boost the performance of those funds. Ritter and Zhang (2007) refer to this conflict of interest as the "nepotism" hypothesis.
- The underwriter may intentionally underprice the IPO when it expects that its affiliated funds will receive IPO shares. To our knowledge this potential conflict has not been investigated before. We label it the "supernepotism" hypothesis.

The nepotism and supernepotism hypotheses are fundamentally different, but not mutually exclusive. Under nepotism, the underwriter bank allocates more IPO shares to its affiliated funds once it realizes that the IPO is underpriced. Under supernepotism, the investment bank underprices the IPO with the intention of allocating underpriced shares to affiliated funds. The bank intentionally imposes a monetary cost on the IPO issuer in order to benefit its asset management arm.

Using a hand-collected dataset of U.S. IPO allocations, we find support for the supernepotism hypothesis in a regression discontinuity design (RDD) setting: a one percentage point increase in IPO allocations to affiliated funds leads to an increase in underpricing of 5.4 percentage points. Our evidence suggests that the conflict of interest inherent in the underwriter-fund manager association has real monetary costs for IPO issuers, in addition to the distortions affecting investors that are documented in the existing literature (Ritter and Zhang (2007)).

To construct our dataset we rely on section 10(f)-3 of the Investment Company Act, which requires investment companies to report their affiliated transactions to the U.S. Securities and Exchange Commission (SEC). Using reports from the SEC EDGAR database, we compile data on all IPO allocations to underwriter-affiliated funds between 2001 and 2013. Our final dataset includes 1,294 IPOs underwritten by 64 underwriters involved in transactions with their affiliated funds.

Identifying the causal effect of affiliated IPO allocations on IPO underpricing is challenging because IPO allocations and IPO offer prices are jointly endogenously determined. As the outcome of profit-maximizing decisions of investment banks, both allocations and offer prices are most likely affected by and correlated with firm characteristics and other unobserved confounding factors. We argue that the 10(f)-3 rule provides the institutional setting needed to single out the causal effect we are interested in identifying. This rule sets a threshold, requiring issuers to be at least three years old before the underwriter is allowed to allocate shares to its affiliated funds. Therefore, the size (and the probability) of underwriter-affiliated allocations jumps discontinuously when the age of the issuing firm is equal to or above the three year cutoff date. We use a fuzzy regression discontinuity design (RDD) to exploit this discrete jump at the cutoff point and estimate the effect of the treatment (affiliated allocations) on the outcome (underpricing), while eliminating any observed or unobserved confounding factors. Intuitively, firms that go public at slightly more than three years of age are arguably similar, on average, to firms that go public at slightly less than three years. Hence, they have similar characteristics and expected underpricing. Because of the 10(f)-3 rule, however, they differ in their underwriter-affiliated allocations. By exploiting the three year cutoff in a fuzzy RDD setting, we can estimate the causal effect of affiliated allocations on underpricing.

Our hand-collected dataset of affiliated IPO allocations also allows us to revisit the dumping-ground and nepotism hypotheses analyzed in the prior literature, especially by Ritter and Zhang (2007). Several prior studies use fund holdings to proxy for initial IPO allocations (Ritter and Zhang (2007), Reuter (2006), Hao and Yan (2012), and Mooney (2015)). These proxies may be imprecise, as the first few days following an IPO typically exhibit strong trading volumes (Ellis et al. (2000)). Moreover, underwriters trying to dump cold shares on an affiliated fund are more likely to do so in aftermarket trading than during an initial IPO allocation, when they would run afoul of the spirit of rule 10(f)-3, which is to protect "fund shareholders by preventing an affiliated underwriter from placing or 'dumping' unmarketable securities with the fund."[4] Hence, the use of secondary-market data (rather than initial allocations) is likely to overstress the relative importance of dumping-ground incentives compared to nepotism incentives. In our dataset of initial IPO allocations, we find strong evidence that nepotism is pervasive in IPO allocations and dominates any dumping-ground incentives. Affiliated funds receive more allocations when IPOs are more severely underpriced, suggesting that the funds are favored by their affiliated investment banks.

[4] See for example https://www.sec.gov/rules/final/ic-25888.htm, section A.3.

We consider three elements that might determine the relative importance to investment banks of the nepotism and dumping-ground conflicts. First, dumping-ground incentives should be stronger when the underwriter is completing an abnormally low number of IPOs (Ritter and Zhang (2007)). In such times, the marginal benefit of completing an additional IPO is higher for the investment bank, which not only receives revenues from the underwriting discount but may also be protecting its reputation. Second, underwriters receive commissions kickbacks when they allocate underpriced shares to independent, meaning unaffiliated, funds (Reuter (2006), Nimalendran et al. (2007), and Goldstein et al. (2011)); this source of revenue dampens their incentive to favor their affiliated funds (Ritter and Zhang (2007)). Accordingly, the nepotism incentive should be weaker when the underwriter receives an abnormally high stream of brokerage commissions from institutional investors. Third, we argue that the relative benefits and costs of affiliated allocations depend on the level of asymmetry in information concerning the issuer's value. When information asymmetry is high, the contribution of affiliated funds to price discovery may be lower than that of independent funds, as the affiliated funds might have access to signals that are highly correlated with those of the underwriters. Nepotism incentives might be relatively low and dumping-ground behavior might rise as a consequence of favoring independent funds to gain increased access to information. Therefore, we postulate that the nepotism conflict weakens as information asymmetry increases.

Overall, we find evidence consistent with these hypotheses. This suggests that while the nepotism and dumping-ground conflicts are likely both at play in the IPO allocation process, the nepotism conflict dominates the other.

2. Literature review and hypothesis development

An increasing body of literature investigates the role played by conflicts of interest within the IPO bookbuilding process, providing extensive evidence that underwriters allocate shares in ways that could be detrimental to issuers. Several researchers examine the hypothesis that underwriters preferentially allocate IPO shares to institutional investors that give back part of the underpricing gains in the form of brokerage commissions (the “commission-kickbacks conflict” hypothesis). Using an event-study methodology, Goldstein et al. (2011) find that underwriters’ brokerage commission revenues are abnormally high in the period preceeding hot IPOs. Consistent with Nimalendran et al. (2007), they find that one of the strategies used to increase commissions is churning shares through round-trip trades in liquid stocks. Moreover, Reuter (2006) and Jenkinson et al. (2018) find a direct positive correlation between the dollar amount of commissions paid by a fund family to an investment bank and the family’s allocations of underpriced IPOs underwritten by the same bank. Griffin et al. (2007) find evidence of the practice known as “laddering,” which involves a quid-pro-quo arrangement between underwriters and their clients: investors receive IPO allocations in exchange far a promise to buy additional shares in the aftermarket. Liu and Ritter (2010) focus on “spinning,” the practice of allocating hot shares to corporate executives to influence their decisions to hire the investment bank for future services; they find that these executives are less likely to switch investment bankers in follow-on offers. Ritter and Zhang (2007) and Mooney (2015) analyze the conflicts of interest involved in the allocation of IPOs to underwriter-affiliated funds, in the U.S. market and worldwide, respectively. Their evidence is mixed. Ritter and Zhang (2007) find some evidence of nepotism (underwriters favor their affiliated funds in the allocation of hot IPOs, mainly during the internet bubble period). Mooney (2015) finds large cross-country differences in the types of conflicts of interest that affect the allocation of IPO shares to affiliated funds.

Another line of research focuses on conflicts of interest between investment banks and their affiliated investment management arms. Consistent with the existence of costly agency problems, Berzins et al. (2013) find that bank-affiliated funds significantly underperform independent funds. Hao and Yan (2012) find one reason behind this underperformance to be that affiliated funds tend to hold a disproportionately large amount of cold equity issues underwritten by their affiliated banks, consistent with dumping-ground behavior.

Our study joins these two lines of research, as we examine the conflicts of interest between issuers, investment banks, and their affiliated investment management companies in the context of IPO allocations to underwriter-affiliated funds. Like Ritter and Zhang (2007), we investigate the conflicts of interest involved in the allocation of IPO shares to underwriter-affiliated funds, and we frame our discussion in terms of the nepotism and dumping-ground conflicts. However, we approach these questions using different hypotheses, methodology, data sources, and the time period covered by our sample.

Our study makes four novel contributions. First, we argue that conflicts of interest incentives may affect IPO pricing, not just IPO allocations to affiliated funds, and we find support for this new hypothesis using a RDD methodology. Second, we construct a direct measure of IPO allocations to affiliated funds using hand-collected data, instead of relying on proxies based on fund holdings. Our empirical analysis allows us to assess the monetary costs of conflicts of interest for issuers. Third, we exploit our data to test some hypotheses that have been developed by prior studies, but have not been directly tested yet; for example, we use trading commission data to directly test that nepotism incentives are weaker when the underwriter receives a high stream of brokerage commissions in the secondary market. Fourth, we develop and test a new hypothesis about the cross-sectional variation of conflicts of interest incentives; that is, nepotism incentives are weaker when the information asymmetry about the issuer's value is higher.

2.1. The effect of the underwriter/affiliated fund conflict of interest on IPO pricing

In the standard IPO bookbuilding procedure, the underwriter has discretion over both the allocation decision and the pricing decision, and it can jointly set the offer price and the amount allocated to its affiliated funds in a way that maximizes its own profits. We postulate that if the underwriter is part of a banking group with an asset management arm, it has an incentive to underprice IPOs so as to benefit its affiliated funds – the supernepotism hypothesis.

Hypothesis 1. *Because of supernepotism incentives, underpricing is an increasing function of the percentage of shares allocated to affiliated funds.*

2.2. Nepotism vs. dumping-ground

Our hand-collected dataset of affiliated IPO allocations also enables us to revisit the dumping-ground and nepotism hypotheses analyzed in the prior literature. On the one hand, underwriters might give preferential treatment to their affiliated funds, giving them hot IPOs to enhance their performance (nepotism hypothesis). Such behavior might be costly for issuers, as their shares would not be allocated according to their best interests. On the other hand, underwriters might dump cold IPOs on their affiliated funds, so that more deals could be completed at the expense of funds' shareholders (dumping-ground hypothesis). These potential conflicts of interest generate two opposite testable predictions. If the nepotism conflict dominates the IPO allocation market, then allocations to underwriter-affiliated funds and underpricing should be positively related. If the dumping-ground conflict dominates the IPO allocation market, then allocations to underwriter-affiliated funds and underpricing should be negatively related. Based on this discussion, we formulate the following hypothesis:

Hypothesis 2. ***(2a)*** *If nepotism incentives dominate dumping-ground incentives, then the correlation between underpricing and the percentage of shares allocated to affiliated funds is positive.* ***(2b)*** *If dumping-ground incentives dominate nepotism incentives, then the correlation between underpricing and the percentage of shares allocated to affiliated funds is negative.*

2.3. Variation in conflict of interest incentives

Ritter and Zhang (2007) argue that the relative weight of these two incentives in the investment bank's profit function depends on the market conditions the underwriter faces. When the underwriter faces a cold IPO market, dumping-ground incentives gain importance, as the marginal benefit of completing an IPO is higher. We build on this intuition to argue that this incentive is underwriter-specific. When the underwriter is completing a low number of IPOs, relative to its normal business, then the pressure to complete IPOs gain importance and the dumping-ground conflict emerges. When the underwriter is completing a high number of IPOs, relative to its normal business, then the benefit of completing an additional IPO is low. The revenues from the management and performance fees of affiliated funds gain weight in the investment bank's profit function and the nepotism conflict stands out. Hence, we formulate the following hypothesis:

Hypothesis 3. *The correlation between underpricing and the percentage of shares allocated to affiliated funds is lower when the underwriter expects to complete a small number of IPOs relative to its normal business.*

Ritter and Zhang (2007) argue that IPO allocations depend on the relative ability of affiliated and independent funds to generate revenues for the investment bank. As the commission-kickbacks conflict gains importance in the underwriter's profit function, the incentive to allocate underpriced shares to affiliated funds is reduced. If the underwriter enters a quid-pro-quo agreement with unaffiliated, independent funds, it might tend to give them preferential treatment in exchange for higher brokerage commission revenues (Reuter (2006), Nimalendran et al. (2007), Goldstein et al. (2011), and Jenkinson et al. (2018)), thus putting nepotism incentives aside. Our access to trading commissions data enables us to test the following hypothesis:

Hypothesis 4. ***(4a)*** *The correlation between underpricing and the percentage of shares allocated to affiliated funds is higher when the underwriter receives a low stream of brokerage commissions in the secondary market.* ***(4b)*** *The correlation between underpricing and the percentage of shares allocated to unaffiliated funds is higher when the underwriter receives a high stream of brokerage commissions in the secondary market.*

In standard information-based bookbuilding theories (such as Benveniste and Spindt (1989)), underpricing is the compensation for the information-revealing indications of interest by institutional investors. We argue that the level of information asymmetry influences conflict of interest incentives because of the roles played by different classes of investors in providing information. In firms with high information asymmetry, the contribution of affiliated funds to price discovery may be lower than that of independent funds. The affiliated funds might have access to signals that are highly correlated with those of their affiliated underwriters, thus making their contribution to price discovery of little value. Nepotism incentives still exist, but they might be relatively low, as the underwriter needs to reward the unaffiliated funds for providing information. Therefore, underwriters might give preferential treatment to independent funds that reveal their signals when information asymmetry is high, thus penalizing the affiliated funds. Some dumping-ground behavior might also arise as a consequence of favoring independent funds. In firms with low information asymmetry, instead, price discovery matters less, giving the underwriter more scope to allocate hot shares to its affiliated funds. Hence, the nepotism incentive might gain importance in the profit function of the investment bank. Based on this argument, we posit that the correlation between underpricing and affiliated allocations should be higher in low information asymmetric firms, while the correlation between underpricing and non-affiliated allocations should be greater in high information asymmetric firms. We formulate the following hypothesis:

Hypothesis 5. ***(5a)*** *The correlation between underpricing and the percentage of shares allocated to affiliated funds is higher when information asymmetry is low.* ***(5b)*** *The correlation between underpricing and the percentage of shares allocated to unaffiliated funds is higher when information asymmetry is high.*

3. Data and summary statistics

Section 10(f) of the investment company act of 1940 prohibits underwriters from selling any shares of a security offering to funds that are in any way affiliated with any member of the syndicate. This regulation was amended in 1958 and in subsequent years to exempt certain transactions. As of today, rule 10(f)-3 permits funds to buy securities underwritten by their affiliated underwriters if certain conditions are satisfied. For the purposes of this research, four of these conditions are of particular importance: (*i*) the issuer must have been in continuous operation for at least three years prior to the offering, including the operations of any predecessors; (*ii*) the securities are offered under a firm-commitment contract;[5] (*iii*) the affiliated transaction has to be executed

[5]In a firm-commitment contract, the underwriter guarantees to purchase all the securities offered by the issuer, regardless of whether or not they can sell them to investors.

by a syndicate member other than the affiliated underwriter;[6] (*iv*) the existence of any transaction pursuant to the 10f-3 rule has to be reported on the form N-SAR of the investment company, attaching a written record of the details of each transaction.

The first three items allow us to identify IPOs that are eligible for 10(f)-3 transactions, that is, IPOs whose shares can be allocated to underwriter-affiliated funds. The last item allows us to hand collect a novel dataset containing data about IPO allocations received by funds affiliated to the underwriters.

In the following subsections, we describe our sample selection criteria, define the main variables used in our analyses, and provide summary statistics.

3.1. IPO data

We use the Thomson Financial Security Data Company (SDC) database to identify IPOs made in the United States from 2001 to 2013.[7] We exclude all American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), unit and rights offerings, closed-end funds, IPOs with SIC codes between 6000 and 6199 and IPOs with offer price smaller than $5. Moreover, we require IPOs to have a match with the Center for Research in Security Prices database (CRSP) within seven calendar days from the issue. These filters leave us with 1,294 IPOs.

From SDC and CRSP we get the name of the issuer and its SIC code, the nation where the issuer is located, the CUSIP and PERMNO numbers of the security issued, the issue date and filing date, the offer price and the original midpoint of the filing price range, the first day closing price, the number of shares issued and whether they are pri-

[6]For example, take issuer X, underwritten by banks A and B. Rule 10(f)-3 says that funds affiliated to bank A can receive allocations only from bank B, and, viceversa, funds affiliated to bank B can receive allocations only from bank A.

[7]We clean the database from known mistakes by manually applying the corrections listed, as of April 2014, on the IPO database managed by Jay R. Ritter at the University of Florida: https://site.warrington.ufl.edu/ritter/ipo-data/.

mary or secondary shares, the total assets of the issuer before the IPO,[8] the primary exchange where the shares are listed, the identity and number of lead managers and other syndicate members, the underwriting gross spread and the type of underwriting contract under which the securities are issued, and a flag identifying venture backed IPOs. We match our sample with data available on the IPO data website managed by Jay R. Ritter at the University of Florida to find the issuers' founding years and the underwriters' reputation rankings.[9] When the founding year is not available on the Ritter website, we complement it with the founding date available on SDC. Underwriters' reputations are coded using numbers ranging from 1 (lowest ranking) to 9 (highest ranking). These rankings are described in Loughran and Ritter (2004) and are an adjustment to the Carter and Manaster (1990) rankings. Table 1 describes the IPO variables we compute by matching the SDC, CRSP, and Ritter data.

[Table 1 about here.]

We define an IPO to be eligible for affiliated transactions pursuant to rule 10(f)-3 if each of the following four conditions is met: (*i*) $Age \geq 3$; (*ii*) $FirmCommitment = 1$; (*iii*) $NumberSyndicateMembers > 1$; (*iv*) at least one lead underwriter has been involved in a 10(f)-3 transaction in our sample.

The first three conditions are a direct consequence of the 10(f)-3 rule's requirements. The rationale behind our fourth condition is that underwriters that have never been involved in 10(f)-3 transactions might not have affiliated funds.[10] From our original sample of 1,294 IPOs, we count 1,086 IPOs that are eligible for affiliated transactions;

[8] When the total assets pre-IPO are missing in SDC, we proxy them by subtracting the total proceeds of the IPO from the total assets after the IPO, taking the latter from COMPUSTAT.

[9] The link is: https://site.warrington.ufl.edu/ritter/ipo-data/

[10] Another possibility is that they do have affiliated funds, but consider the costs of allocating shares to them to be too high (such as the costs of compliance with the 10(f)-3 rule).

208 IPOs do not satisfy at least one of the four requirements. Figure 1 plots the number of IPOs by year, distinguishing between in eligible and non-eligible IPOs.

[Figure 1 about here.]

The total number of IPOs per year varies considerably, ranging from 21 in 2008 to 169 in 2004. The percentage of eligible IPOs, at about 84% on average, appears to be stable in the period 2001-2013.

Table 2 provides summary statistics on our sample of IPOs, breaking them down into eligible IPOs (Panel A) and non-eligible IPOs (Panel B). All non-dummy variables except *Age* are winsorized at the 95% level.[11] Table 2 shows that non-eligible IPOs differ from eligible IPOs in that they are smaller and younger, have lower underpricing, and are less likely to be underwritten by a top-ranked underwriter.

[Table 2 about here.]

3.2. Allocations data

Investment companies report their affiliated transactions to the Securities and Exchange Commission (SEC) through the N-SAR filings. We download from the SEC EDGAR database all the N-SAR forms filed from January 2001 to December 2014 and collect data on affiliated IPO allocations in the period 2001-2013. (Appendix A explains the downloading, parsing, and matching procedures.) Using this data, we build our Affiliated Allocations dataset, which contains: IPO identifiers (issuer name, CUSIP, and issue date); the name of the affiliated fund and/or the sub-portfolio of the fund and/or the investment company that receive an allocation; the number of shares received by the affiliated fund and/or by the sub-portfolio of the fund and/or by the

[11] We do not winsorize *Age* because it is the forcing variable in the RDD of section 4.

investment company the fund is managed or advised by; the name(s) of the affiliated underwriter(s); and the name(s) of the underwriter(s) from whom the shares were purchased, often referred to as the "broker" in the N-SAR filings. Hence, we observe the number of shares allocated at the IPO-investor-broker level.

For the purposes of this paper, in our main analyses we aggregate affiliated allocations at the IPO level, letting A_i be the total number of shares allocated to affiliated funds in IPO i. Then we build the two main variables of our analysis: $AffiliatedAllocPerc$ and $AffiliatedAllocDummy$. The variable $AffiliatedAllocPerc$ is the percentage of the issue allocated to affiliated funds. If N_i is the number of shares issued in IPO i, then:

$$AffiliatedAllocPerc_i = 100\frac{A_i}{N_i}$$

For robustness, we also use the variable $AffiliatedAllocDummy$, which is a dummy variable equal to one if at least one share is allocated to an affiliated fund:

$$AffiliatedAllocDummy_i = \mathbb{1}(A_i > 0)$$

The N-SAR filings provide information about affiliated allocations only. We also build a proxy for the percentage of the issue allocated to independent funds, that is, to funds not affiliated with the underwriters of a given IPO. First, we match the SDC sample to the Thomson Financial CDA/Spectrum 1&2 database (s12) using CUSIP numbers. Then we compute the total holdings held by mutual funds at the first reporting date after each IPO, excluding non-U.S. mutual funds and mutual funds with investment codes of 5, 6, or 8, letting H_i be the total number of shares held by mutual funds in company i at the first reporting date after the IPO of company i. Then we build a proxy for the percentage of the issue allocated to independent funds as:[12]

$$IndependentAllocPerc_i = 100\frac{H_i - A_i}{N_i}$$

In order to reduce the impact of potential data errors and outliers, we winsorize the allocation variables $AffiliatedAllocPerc$ and $IndependentAllocPerc$ at the 95% level.

Table 3 summarizes the allocation data at the issuer level for the 1,086 eligible IPOs (Panel A) and the 208 non-eligible IPOs (Panel B). Panel (A) reports that 611 IPOs, about 56% of the eligible IPOs, involve at least one affiliated transaction and, on average, 1.44% of the issue is allocated to funds affiliated with the underwriters. This implies that, conditional on involving at least one 10(f)-3 transaction, the average percentage allocated to affiliated funds is 2.57% (1.44 divided by 0.56). The median affiliated allocation is lower than the mean, indicating a positive skewness. The average percentage of the issue allocated to independent funds is 18.3%.

Panel (B) reports the same statistics for non-eligible IPOs. Interestingly, underwriters allocate shares of non-eligible IPOs to their affiliated funds in 17 IPOs, about 8% of such IPOs. Eight of these IPOs do not satisfy the age requirement, being less than three years old. There are several reasons why underwriters might have allocated shares to their affiliated funds in these cases. First, these IPOs may be misclassified as "non-eligible". Errors in the issuers' founding dates or the existence of unknown predecessors could have led us to miscalculate the issuers' age. A second possibility is that the age is correct, but no enforcement action was recommended by the SEC. In a private conversation, an SEC expert pointed out that the Securities and Exchange Commission

[12]This proxy is noisy for two reasons. First, it is affected by aftermarket trading of both affiliated and unaffiliated funds. Second, it is affected by the different coverage of funds in our Affiliated Allocations dataset and in the s12 database.

takes into account the general principles behind the 10(f)-3 rule when interpreting and applying it. Consequently, certain transactions that seem to formally violate the rule could, in fact, be allowed.[13] A third possibility is that underwriters might have broken the 10(f)-3 rule in these cases, allocating shares of non-eligible issuers to their affiliated funds. A search on Google provides information consistent with the founding dates contained in our dataset, and we decide to flag these eight IPOs as non-eligible.

One of the 17 non-eligible IPOs does not satisfy the firm commitment requirement, while the remaining eight non-eligible IPOs do not satisfy the lead underwriter requirement, meaning that none of their lead underwriters has ever been involved in a 10(f)-3 transaction in our sample. In these eight IPOs, affiliated transactions involve other syndicate members only.

[Table 3 about here.]

Figure 2 shows the average allocations to affiliated and independent funds over the period 2001-2013 for the 1,086 eligible IPOs. Panel (A) shows that the percentage of IPOs with affiliated allocations ranges from a minimum of 41% in 2008 to a peak of 77% in 2009, with no apparent trend in the period 2001-2013. The average percentage allocation to affiliated funds ranges from a minimum of 0.87% in 2005 to a peak of 2.72% in 2009 and behaves similarly to the average percentage of the issue allocated to affiliated funds conditional on IPOs involving at least one affiliated transaction. This

[13] One popular example dates back to 2008, when the Goldman Sachs Trust requested assurance that the SEC would not have recommended any enforcement action related to some affiliated allocations of fixed-income securities issued by companies that were less than three years old. These securities were co-issued with and 100% guaranteed by another company that was more than three years old and, thus, was compliant with the 10(f)-3 rule. The SEC concluded that the characteristics of the co-issue and the 100% guarantee were consistent with the aim of the rule, which is to avoid unmarketable securities being dumped to affiliated funds. Hence, it assured Goldman Sachs that it would not have recommended any enforcement action. See the SEC's interpretative letter for more details:
https://www.sec.gov/divisions/investment/noaction/2008/goldmansachstrust081908.htm

means that in periods when underwriters are more likely to allocate some shares to their affiliated funds, the size of the affiliated allocations tend, on average, to be larger.

We notice no apparent increase in affiliated allocations after 2003, when the SEC amended the 10(f)-3 rule, loosening some of its constraints. In particular, after 2003 the maximum amount of shares that an underwriter can allocate to its affiliated funds (the "percentage limit," or 25% of the issue) applies to the principal underwriter only. This constraint is not binding in the IPO allocations market, as affiliated allocations are far below the percentage limit imposed by the 10(f)-3 rule.

While affiliated allocations do not show a clear trend over the time period of our sample, we do notice that the percentage of the issue allocated to independent funds has sharply increased in recent years, from about 15% before 2010 to almost 25% afterward.

[Figure 2 about here.]

To assess the contribution of our novel dataset, it is worth comparing these summary statistics with those of Ritter and Zhang (2007), as they used the Spectrum 1&2 holdings to proxy for affiliated allocations. The only overlapping year between our research and theirs is 2001. Ritter and Zhang (2007) find that affiliated funds report positive holdings for approximately 26% of the IPOs in 2001, while the true percentage of IPOs involving affiliated allocations, based on N-SAR filings, is about 71%. Moreover, they find that the average allocation - conditional on the allocation being greater than zero - is 0.7%, while according to the N-SAR filings it is 2.93%. These numbers suggest that using the Spectrum 1&2 holdings to proxy for affiliated allocations might considerably understate their prevalence and size.

The reader may refer to the Web Appendix (https://tinyurl.com/webappendixnepotism) for additional summary statistics .

4. The effect of affiliated allocations on underpricing

In section 2, we posit that underwriters might underprice IPOs in order to increase their affiliated funds profits (Hypothesis 1). In order to test this supernepotism hypothesis and identify a causal link between affiliated allocations and underpricing, we need to find a source of exogenous variation in affiliated allocations.

Rule 10(f)-3 provides the institutional setting we need to the design a quasi-experiment. The rule requires issuers to be at least three years old for the underwriter to be permitted to allocate shares to its affiliated funds. Hence, the probability of allocating some shares to affiliated funds might discontinuously increase at the cutoff point, thus allowing us to implement a fuzzy regression discontinuity design (RDD).[14]

In order to introduce the RDD terminology, we use the following terms interchangeably: $Underpricing$ is the "outcome" variable; our affiliated allocations measures – $AffiliatedAllocPerc$ and $AffiliatedAllocDummy$ – are the "treatment" variables; and Age is the "forcing" (or "running") variable that determines the assignment-to-treatment status through the three year cutoff. We are interested in the causal effect of the treatment on the outcome variable. The fuzzy RDD exploits the discontinuous variation in the treatment status provided by the forcing variable at the three-year cutoff point in order to identify that causal effect.

The RD framework allows us to approximate an ideal experimental setup, where the possibility of allocating shares to underwriter-affiliated funds is randomly assigned, thus helping us overcome the joint endogeneity of affiliated allocations and underpricing. Consider an underwriter who is hired by firms of random ages in order to perform their IPOs. Firms that choose to go public at two years old probably differ, in several

[14] As observed in section 3, the three year cutoff does not perfectly determine the affiliated allocation decision, neither below nor above the threshold. Hence, a sharp RDD does not fit our setting.

dimensions, from those that go public when they are in their twenties. These IPO-specific differences may influence both the allocation and the pricing decisions of the underwriter, thus making it difficult to identify causal effects. If we consider an arbitrarily small neighborhood around the three year cutoff point, however, we can compare firms that differ discontinuously in their treatment status (that is, firms just above and just below the cutoff point), but do not differ discontinuously along other dimensions.

The identification assumption is that only the treatment (the affiliated allocations) changes discontinuously at the cutoff point, while the conditional expectation function of other unobservable and observable factors is continuous. If there is some randomness in the age of the IPO firm around the cutoff, that is, if the underwriter has only imprecise control over the age of the firm at the offer date, then the conditional expectation function of other factors is indeed continuous in the forcing variable (Lee and Lemieux (2010)). We discuss the validity of this identification assumption in section 4.1.

Our identification strategy is illustrated in Figure 3. Consider an underwriter that faces nepotism incentives and which has a profit function such that:[15] *i)* its optimal choice of the offer price, P, as a function of the affiliated allocation, A, is given by the line $P^*(A)$; *ii)* its optimal choice of A, as a function P, is given by the line $A^*(P)$. If the underwriter complies with the 10(f)-3 rule, its affiliated allocations are constrained to zero when the age of the IPO falls just below the cutoff. In this case, the affiliated allocation and the optimal price are given by the pair $(0, P_0)$. When the age of the IPO is just above the cutoff, instead, the underwriter can optimally choose P and A to maximize its profits, that is, it chooses the pair (A_1, P_1). Hence, the cutoff identifies movements along the $P^*(A)$ function, thus allowing us to estimate its slope, that is, to estimate the change in the optimal offer price caused by a change in the allocation

[15]For the sake of simplicity, we rule out dumping-ground incentives for the purposes of this illustration.

to affiliated investors. Since we implement a fuzzy RDD, we estimate a Local Average Treatment Effect (LATE), that is, the effect of affiliated allocations on underpricing for units that comply to the 10(f)-3 rule.

[Figure 3 about here.]

For the purposes of this section, we restrict the sample to eligible IPOs (1,086 observations) and IPOs that are not eligible because they do not meet the age requirement (65 observations), that is, syndicated IPOs issued under a firm-commitment contract whose lead underwriters have been involved in at least one 10(f)-3 transaction in our sample. In this way, we focus the RDD analysis on observations for which the three year cutoff is binding.

The remaining 143 IPOs are not eligible regardless of their age, as they do not meet at least one of the other 10(f)-3 requirements. The cutoff is not binding for them and they are useful for placebo tests only.

4.1. Relevance and exogeneity: graphical analysis and discussion

We follow the RDD literature (Imbens and Lemieux (2008) and Lee and Lemieux (2010)), providing graphical evidence that supports the relevance and exogeneity of the three year threshold.

For the cutoff to be a valid instrument in a fuzzy RDD, it must discontinuously affect the treatment variable. Figure 4 plots the average value of the variables $AffiliatedAllocDummy$ and $AffiliatedAllocPerc$ by one year age groups (bins). Panel (A) shows that the probability of receiving the treatment jumps at the cutoff. The probability that an IPO involves a 10(f)-3 transaction is less than 20% for IPOs below the threshold, but jumps to more than 50% just above the threshold. A similar pattern holds for the average percentage of the issue allocated to affiliated funds (Panel (B)): it is smaller than 0.5% below the cutoff, but jumps to much more than 1% above the cutoff.

[Figure 4 about here.]

If the cutoff affects underpricing through a discontinuous change in affiliated allocations, then we should observe a jump in the outcome variable at the cutoff point (this is known as the intent-to-treat effect). Figure 5 plots the average underpricing by age bins. Underpricing shows a large, clear jump at the cutoff, from about 5% to more than 15%. This jump in underpricing at the cutoff point is consistent with supernepotism. It cannot be explained by nepotism.

[Figure 5 about here.]

The exogeneity of the cutoff is not testable. However, we can check to see if the implications of exogeneity hold in our setting.

In principle, the three year cutoff could be endogenous. Underwriters do have some control over the length of the IPO process, and they might time their IPOs so as to make them eligible for 10(f)-3 transactions. Although appealing, this argument is not supported by empirical evidence. If underwriters were manipulating the length of the IPO process, then we would see a jump or spike in the variable $LengthIPOprocess$ at the cutoff point: three-year-old firms would experience longer IPO processes because of their underwriters' timing strategy. Figure 6, Panel (B), shows this not to be the case. There is no evidence of a jump or spike at the cutoff point.

[Figure 6 about here.]

Another possibility, however, is that the underwriter might manipulate the age of the issuer by postponing the filing date and the beginning of the IPO process. This would leave the length of the IPO process unchanged for three-year-old firms, thus preventing us from detecting their manipulation in Figure 6, Panel (B) and invalidating our design.

We find this argument not convincing for three reasons. First, underpricing the IPO is not the underwriter's sole objective. The underwriter also wants to accomplish the IPO and not miss a window of opportunity. This pushes the underwriter to not delay the start of the IPO process, as the issuer might turn to a competing underwriter in order to complete its IPO. Thus, competition among underwriters to get deals reduces the scope for manipulation. Second, the RDD setting is invalid only if underwriters can precisely manipulate the assignment variable (Lee and Lemieux (2010)). It is unlikely that an underwriter could do so before starting the IPO process, as the length of the process is a random variable over which the underwriter does not have full control.[16] Third, if underwriters were systematically manipulating the IPO age, then we would observe a jump in the density of the variable *Age* at the cutoff point. Figure 6, Panel (A), shows that this is not the case: there seems to be no jump in the density of *Age* at the three year threshold, suggesting that *Age* manipulation by underwriters is unlikely to be systematic. Figure 7 plots by age bin the number of IPOs underwritten by the most important underwriters:[17] there seems to be no general jump in the number of IPOs underwritten by each underwriter at the cutoff point; only Wells Fargo shows a spike there. Overall, the non-manipulation evidence seems to hold also at the underwriter level.

[Figure 7 about here.]

The identification assumption of the RD design is that the conditional expectation functions of observable and unobservable factors related to the outcome (other than

[16]The random component in the length of the IPO process includes factors that make it not fully predictable, such as the processing capacity of the SEC, indications of interest collected during the bookbuilding process, last minute news, pressures from the firm to complete the IPO, etc.

[17]The fourteen most important underwriters are defined as those that are involved in 10(f)-3 transactions in at least 25 IPOs in our sample. See the Web Appendix (https://tinyurl.com/webappendixnepotism) for additional details.

the treatment) are continuous at the cutoff point. We cannot test whether this assumption holds for unobservable factors, but in Figure 8 we plot the average value of the observable covariates by age bins. The figure shows no clear jump in the conditional expectation function of any of the covariates. Interestingly, the main predictor of underpricing – the variable *Adjustment* – is continuous at the cutoff point. Some variables ($NumberLeadManagers$ and $NumberSyndicateMembers$) show a spike at the three year threshold, but this spike does not seem to be a jump in the conditional expectation function, which might plausibly be continuous. Overall, the expectation functions of the covariates conditional on age do not seem to be discontinuous at the cutoff point.

[Figure 8 about here.]

Another identification concern that we need to address is the following. The goal of the 10(f)-3 rule is to prevent underwriters from dumping unmarketable securities on their affiliated funds. Hence, the regulators might have chosen the three year threshold exactly because IPOs in their early stages of life are more likely to be unmarketable, thus resulting in lower average underpricing. This argument, though plausible, does not in itself affect the RD design, which focuses on the discontinuities at the cutoff point. It suggests, however, that it might be important to control for the underlying relation between underpricing and age in our regressions.

4.2. Local linear IV results

In this subsection, we estimate the effect of underwriter-affiliated allocations on underpricing in a fuzzy RD design.

Let x_i be the age of firm i at the IPO date minus the cutoff level, $x_i = Age_i - 3$, and let z_i be a dummy variable identifying firms that are at least three years old, $z_i =$

$\mathbb{1}(x_i \geq 0)$. We then estimate several specifications of the following local linear IV model, where $Alloc_i$ is one of our two measures of affiliated allocations, $AffiliatedAllocPerc_i$ or $AffiliatedAllocDummy_i$, and $Underpricing_i$ is the first day return:

$$\begin{cases} Underpricing_i = \beta_0 \ + \ \beta_1 Alloc_i \ + \ \beta_2 x_i \ + \ \beta_3 z_i x_i \ + \ e_i \quad with \ x_i \in [-h, h-1] & (1) \\ Alloc_i = \gamma_0 + \ \gamma_1 z_i \ + \ \gamma_2 x_i \ + \ \gamma_3 z_i x_i \ + \ v_i \quad with \ x_i \in [-h, h-1] & (2) \end{cases}$$

Based on the discussion and the graphical evidence presented in our previous subsection, we assume that $\mathbb{E}(e_i|x_i)$ is continuous at the cutoff point. Following Imbens and Lemieux (2008), we estimate the model via 2SLS, using z_i as the instrumental variable for $Alloc_i$, in a neighborhood of the cutoff.

Our setting faces three distinct challenges. First, the forcing variable Age is discrete: we observe it only at the year level. Second, Age is measured with noise: given its definition (see Table 1), some truly n-year old firms might fall into the $n+1$ age bin. This might generate some misclassification around the cutoff. Third, the number of values that the forcing variable can take around the threshold is low: it can only take three distinct values below the cutoff. These three issues affect our choice of the bandwidth and standard errors to use.

Concerning the bandwidth size, h, we face a trade-off that goes beyond the usual one related to the sample size, between bias and variance. If we choose $h = 1$, then we use observations relatively close to the cutoff point, which are more likely to meet the random assignment condition. However, given the discrete nature of our forcing variable, we cannot control for the underlying relation between $Underpricing$ and x. If we choose $h > 1$, for example $h = 3$, then we can control for a local linear relation between the outcome variable and the discrete forcing variable. However, we do so at the cost of using observations relatively far from the cutoff point, which are less likely to meet the random assignment condition.

Concerning standard errors, clustering by the forcing variable is popular in the literature on RDD with discrete running variables (Lee and Card (2008)). However, Kolesàr and Rothe (2018) warn that clustering by the forcing variable can lead to serious over-rejection problems when the number of clusters is low. In particular, they show that clustered standard errors perform worse than robust standard errors. We run simulations (unreported here) and confirm that Kolesàr and Rothe's concerns persist in our particular setting, with its low number of clusters and its misclassification around the cutoff. We find that clustered standard errors face a major over-rejection problem, while robust standard errors seem to be fairly conservative in our setting. However, the power of our test is very low when we choose $h = 2$ or $h = 3$ and control for the underlying relation between underpricing and age.[18]

Based on this discussion, we use robust standard errors and we perform our analysis using three symmetric bandwidth levels ($h = 1$, $h = 2$, and $h = 3$), in order to check the robustness of the results in regards to the particular problems we face. Table 4 reports the results of the local 2SLS estimation for different values of the bandwidth.

[Table 4 about here.]

Consistent with the supernepotism hypothesis, Hypothesis 1, the coefficients of our affiliated allocation variables are positive in all specifications; they are statistically significant at conventional levels in all specifications but one, probably due to a lack of power. Focusing on model (6) of Panel (A), which controls for changes in the underlying relation between the outcome and the forcing variable, we find that a one percentage point increase in the fraction of the issue allocated to affiliated funds increases under-

[18]Our simulations show that the power of a two-sided 5% test can be as low as 15%, depending on parameter values.

pricing by about 5.4 percentage points. Table 4 also reports the first-stage F statistic, which is always bigger than 10, suggesting that the instrument z is not weak.

For completeness, Table 5 reports the estimates of the reduced-form regression (Equation (3)). Results are overall consistent with Figure 5 and Table 4.

$$Underpricing_i = \theta_0 \; + \; \theta_1 z_i \; + \; \theta_2 x_i \; + \; \theta_3 z_i x_i \; + \epsilon_i \quad with \; x_i \in [-h, h-1] \quad (3)$$

[Table 5 about here.]

As a benchmark for judging the size of the LATE effect, we estimate the control complier mean (CCM) (Katz et al. (2001)): the average underpricing of IPOs below the cutoff whose underwriters would have allocated shares to affiliated funds if they had been eligible for 10(f)-3 transactions. First, we use the estimates $(\hat{\gamma}_0, \hat{\gamma}_1)$ from the first-stage regression of Table 4, Panel (B), using the $h = 3$ bandwidth (Equation (2)).

Second, we limit the sample to IPOs that are not allocated to affiliated funds. On the right hand side of the cutoff, we have IPOs that are eligible for 10(f)-3 transactions, but nevertheless are not allocated to affiliated funds (never-takers). On the left hand side of the threshold, we have IPOs that are not eligible for 10(f)-3 transactions and are not allocated to affiliated funds (a mixture of compliers and never-takers). We estimate the reduced-form regression (Equation (3)) on this subsample, using a bandwidth level of $h = 3$. Let $(\hat{\theta}_0, \hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3)$ be the estimated parameters on this subsample.

Letting $\hat{\kappa} = (1 - \hat{\gamma}_0 - \hat{\gamma}_1)/(1 - \hat{\gamma}_0)$ be the percentage of never-takers among IPOs that are not eligible for 10(f)-3 transactions and are not allocated to affiliated funds, we estimate the CCM as:

$$CCM = \frac{\hat{\theta}_0 - \hat{\theta}_1 \hat{\kappa}}{1 - \hat{\kappa}}$$

and find $CCM = -6.8$. This result suggests that IPOs whose shares are allocated to affiliated funds because of the 10(f)-3 rule would be on average overpriced by 6.8 percentage points if they were not eligible. By adding the LATE evaluated at the mean value of $AffiliatedAllocPerc$ for complier IPOs, which is equivalent to the coefficient of $AffiliatedAllocDummy$, we find the treated complier mean (TCM): $TCM = CCM + 24.8 = 18$. The 10(f)-3 rule moves the average underpricing of compliers from -6.8% to 18%. Section 4.5 discusses how realistic our RDD estimates are.

4.3. Placebo IPOs

If the three year threshold affects underpricing only through affiliated allocations, then we should observe no jumps in the outcome variable when the cutoff is not binding.

Underwriters of non-eligible IPOs (such as non-syndicated IPOs) cannot allocate shares to their affiliated funds, regardless of the age of the issuer. Hence, there should be no jump in underpricing at the cutoff for these non-eligible IPOs. Figure 9 plots the average underpricing by age bins for non-eligible IPOs: we see no evidence of discontinuities at the three year threshold.

[Figure 9 about here.]

The three year threshold is set by the 10(f)-3 rule and is specific to U.S. regulations. Therefore, we should observe no jump in underpricing at the three year cutoff for non-U.S. IPOs. We verify this fact using a SDC sample of 488 European IPOs issued in the period 2001-2013.[19] In Figure 10 we plot their average underpricing by age bins and we find no evidence of discontinuities at the three year threshold.

[Figure 10 about here.]

[19] In addition to the usual filters, we require the founding date to be non-missing in the SDC database. We compute underpricing using the closing prices available in SDC.

Following the RDD literature (Imbens and Lemieux (2008)), we check that there are no jumps at non-discontinuity points, that is, where the effect on underpricing should be zero. We define three arbitrary thresholds: the median value of age conditional on $Age > 3$, which is 11 years; the 25th percentile of age conditional on $Age > 3$, which is 7 years; and the 75th percentile of age conditional on $Age > 3$, which is 25 years. Figure 11 plots the average underpricing by age bins around these arbitrary thresholds and we see no evidence of discontinuities.

[Figure 11 about here.]

4.4. Robustness checks

Dong (2015) shows that the conventional fuzzy RDD estimator may be biased when the running variable is discrete and rounded down. However, the bias is equal to zero when the slopes (and higher derivatives) of the outcome and the treatment, as functions of the forcing variable, do not change around the cutoff. In Table 4, we notice that the coefficient for the forcing variable x is weakly significant in only one specification, while the interaction term z_x is not statistically different from zero. Hence, we do not expect this bias to significantly affect our results. Two additional pieces of evidence suggest that the discretization of the forcing variable does not affect our conclusions.

Dong (2015) derives a formula to correct for the bias that arise when the running variable is discrete. Under standard assumptions, the fuzzy RDD local average treatment effect can be expressed as the ratio between the intent-to-treat effect (θ_1) and the coefficient of the first-stage regression of the treatment variable on the assignment-to-treatment variable (γ_1): $\hat{\beta}_{FRD} = \frac{\hat{\theta_1}}{\hat{\gamma_1}}$. Dong shows that this ratio is biased when the forcing variable is discrete and rounded. The direction of the bias depends on the change in the slope (and higher derivatives) of the outcome and the treatment, as functions of the forcing variable, around the cutoff. In order to implement Dong's correction, we need to assume a polynomial relation between underpricing and age. Given the structure of our data, we consider the case of a linear relation only. In this case, Dong's bias-corrected version of $\hat{\beta}_{FRD}$ can be computed as:

$$\hat{\beta}_{FRD} = \frac{\hat{\theta}_1 \; - \; \frac{1}{2}\hat{\theta}_3}{\hat{\gamma}_1 \; - \; \frac{1}{2}\hat{\gamma}_3}$$

where $(\hat{\gamma}_1, \hat{\gamma}_3)$ and $(\hat{\theta}_1, \hat{\theta}_3)$ are estimated via Equations (2) and (3), respectively.

Focusing on the $h = 3$ case, we find that the linear correction changes the estimated FRD coefficient of $AffiliatedAllocDummy$ from 24.8 to 27.35. The coefficient of $AffiliatedAllocPerc$ changes from 5.43 to 6.1. The bias, if any, seems to work against finding results, thus suggesting that our results in section 4.2 are conservative.

For a small subsample of 280 IPOs, we know the exact founding date at the *mm/dd/yyyy* level and can compute the precise age of the firm at the issue date; 33 of these IPOs fall within the one-year bandwidth around the cutoff point. Table 6 replicates the fuzzy RDD analysis of section 4.2 for these 33 IPOs.[20] Given their precise age, we can, in principle, control for the underlying relation between underpricing and age within the one-year bandwidth. However, the small sample size might affect the statistical significance of the estimates and the validity of the instrument. Hence, these results should be interpreted very cautiously.

[Table 6 about here.]

The coefficients of $AffiliatedAllocPerc$ and $AffiliatedAllocDummy$ are always positive in all specifications. We notice that the estimates of model (1) are very similar in magnitude to the results reported in Table 4. The statistical significance is weaker

[20]The bandwidth selector proposed by Calonico et al. (2014) would include 29 IPOs with age between 2.1 and 3.9 years. This is very close to the one-year bandwidth that we use for consistency with our baseline analysis.

because of the smaller sample size. The results of model (2) and model (3) are qualitatively consistent with section 4.2, but their estimates are statistically insignificant. Moreover, the magnitudes are implausible in some specifications. We acknowledge that the instrument z becomes weak in models (2) and (3), when we introduce x and z_x as control variables in the first-stage regression. Model (3), in particular, suffers from multicollinearity. Nevertheless, Table 6 suggests that the positive effect documented in section 4.2 is unlikely to be driven entirely by the discrete nature of our forcing variable.

Our main treatment variables ($AffiliatedAllocPerc$ and $AffiliatedAllocDummy$) measure allocations to underwriter-affiliated funds without distinguishing the role played by the affiliated underwriter in the syndicate. Hence, Table 4 implicitly assumes that the lead managers set the IPO offer price while acting in the interests of the underwriting syndicate as a whole. If the lead managers act in their own interests, however, they may choose the IPO price to maximize their own profit as a function of the allocations received by their own affiliated funds. For robustness, Table 7 replicates the fuzzy RDD analysis of section 4.2, using as the treatment variable the allocation received by funds affiliated with the lead underwriters only. If anything, our second stage results are stronger. However, we acknowledge that the instrument becomes weak in some specifications of Panel (A), according to the first stage F statistic. The reason is that the percentage of the issue allocated to funds affiliated to the lead underwriters is about as half as the percentage of the issue allocated to affiliated funds as a whole, thus reducing the jump of $AffiliatedAllocPerc$ around the cutoff.

[Table 7 about here.]

4.5. How realistic are our RDD estimates?

How realistic are our RDD estimates of the causal effect of IPO affiliated allocations on underpricing? In order to address this question we analyze two points: (1) is the percentage of IPO shares allocated to affiliated funds too small to motivate the banks to underprice the IPO?; (2) are the benefits to the underwriting banks sufficiently large to justify (in the eyes of the banks) the cost to the IPO issuer in foregone IPO proceeds? We examine these points by comparing IPO affiliated allocations with another well-documented cause of IPO underpricing: the preferential allocation of underpriced IPO shares to institutional investors, which give back part of their profits to the banks in the form of brokerage commissions. Finding a similar benefit/cost ratio for IPO affiliated allocations and commission kickbacks would support the realism of our RDD estimates. The Web Appendix (https://tinyurl.com/webappendixnepotism) provides the details of our calculations.

Is the percentage of IPO shares allocated to affiliated funds too small to motivate the banks to underprice the IPO significantly more? In the case of commission kickbacks, based on the estimates in Reuter (2006) the average percentage of allocations that went to institutions that gave a kickback to the underwriting bank is 1.8%. This number is very similar to the average percentage of allocations to affiliated funds in our sample.

Are the benefits to the underwriting banks sufficiently large to justify (at least in the eyes of the banks) the cost to the IPO issuer in foregone IPO proceeds? For both commission kickbacks and affiliated allocations, we attempt at roughly estimating the benefits to the banks as a ratio of the cost to the issuing company. We refer below to this ratio as B/C. Relying on the research on commission kickbacks (especially Goldstein et al. (2011) and Reuter (2006)), our estimates of the average B/C ratio range from 0.2% to 3.6%.

In the case of IPO affiliated allocations, based on our RDD results we estimate of the average foregone IPO proceeds due to IPO affiliated allocations at $14 million. The banks benefit thanks to the boost in performance to their affiliated funds from the underpriced IPO shares, which translates into larger fund flows and management fees. For the subset of our funds that we can reliably match to the CRSP Mutual Funds database, we find that on average an affiliated fund invests 0.8% of its assets in an IPO, and that this investment boosts its performance by 1.1% in that year. Using estimates from Del Guercio and Tkac (2002), this performance boost translates into an incremental $0.2 million in management fees for all the affiliated funds that receive allocations in a given IPO. Therefore, for the IPO underwriters the B/C ratio is about 1.4% (0.2/14), which is in the same range as the B/C number we find for commission kickbacks.

Overall, however egregious the practice of underpricing IPOs for the benefit of banks may seem, the calculus of the financial impact for the underwriters and the issuer is similar in the case of IPO affiliated allocations and commission kickbacks. Given that this latter practice has been well documented, we conclude that our RDD estimates are realistic.

5. Nepotism and dumping-ground incentives

We now revisit two hypotheses analyzed in prior work: a milder version of the nepotism hypothesis, and the dumping ground hypothesis. According to the former, underwriters will tend to allocate underpriced shares preferentially to their affiliated funds to boost their performance. According to the latter, underwriters will tend to allocate overpriced shares to their affiliated funds to ensure the success of the IPO. Both these hypotheses have affiliated allocations as the outcome variable. A natural specification would then have a measure of affiliated allocations as the dependent variable, and underpricing as one of the explanatory variables. However, Ritter and Zhang (2007) argue that such a specification could be misleading, as the coefficient of underpricing would capture also the relation between initial IPO returns and allocations to institutional investors as a whole. Building on the empirical model of Aggarwal et al. (2002), they propose to circumvent this issue by regressing underpricing on affiliated allocations, and controlling for independent allocations to capture any private information institutional investors may have. We follow their approach in our analyses.

We first assess which of the two conflicts of interest dominates the IPO market (subsection 5.1). Then we analyze how variation in conflict of interest incentives affects IPO allocations to affiliated funds (subsections 5.2 and following).

5.1. Nepotism or dumping-ground?

In order to assess which type of conflict of interest, nepotism or dumping-ground, is more pervasive in the IPO market, we follow Ritter and Zhang (2007) and estimate several specifications of the following reduced-form model at the IPO level:

$$\begin{aligned} Underpricing = \beta_0 \ + \ \beta_1(Alloc) \ + \ \beta_2(IndependentAllocPerc) \\ + \ \beta_3(Controls) \ + \ \beta_4(indFE) \ + \ \beta_5(yearFE) \ + \ \beta_6(uwFE) \ + \ u \quad (4) \end{aligned}$$

where $Underpricing$ is the first day return and $Alloc$ is either one of our two measures of affiliated allocations: the percentage of the issue allocated to affiliated funds, $AffiliatedAllocPerc$, or a dummy variable identifying IPOs with affiliated allocations, $AffiliatedAllocDummy$. Under the null hypothesis of no conflict of interest, there should be no relation between underpricing and allocations to affiliated funds at the IPO level: $\beta_1 = 0$. The nepotism hypothesis predicts a positive relation between underpricing and affiliated allocations (Hypothesis 2a), $\beta_1 > 0$, while the dumping-ground hypothesis predicts a negative relation between underpricing and affiliated allocations (Hypothesis 2b), $\beta_1 < 0$. Control variables and fixed-effects dummies are described below. We estimate the model via OLS. Since we reject the null hypothesis of homoskedasticity of the error term u, we use robust standard errors for inference.[21] Results are reported in Table 8.

[Table 8 about here.]

Our affiliated allocation measures, $AffiliatedAllocDummy$ and $AffiliatedAllocPerc$, have a positive coefficient in all specifications, providing evidence that the nepotism conflict dominates the dumping-ground conflict. The coefficient estimates are statistically significant either at the 1% or the 5% level. They are also economically significant. If we consider the most conservative estimates, underpricing is 6.28 percentage points higher when underwriter-affiliated funds receive shares in an IPO. Moreover, a one percentage point increase in the fraction of the issue allocated to affiliated funds is associated with a 0.62 percentage point increase in underpricing, meaning that affiliated allocations account for 6.3% of average underpricing.[22]

We include in all specifications the percentage allocation received by non-affiliated funds, $IndependentAllocPerc$, in order to control for the effect of private information possessed by financial institutions. Consistent with Aggarwal et al. (2002), we find that $IndependentAllocPerc$ is positively related to underpricing in all regressions and the coefficient estimates are statistically significant at the 1% level. This result is in line with the partial adjustment literature (Hanley (1993)): financial institutions seem to have private information which is not fully incorporated into the offer price during the bookbuilding process. It is also consistent with the conflicts of interest literature, as the positive coefficient might be driven by underwriters favoring some clients with the allocation of underpriced shares (Reuter (2006), Goldstein et al. (2011)). We shed more light on these two potential interpretations in the next subsections.

[21] In unreported tables, we also use industry-year clustered standard errors and bootstrapped standard errors, with similar findings.

[22] This number is computed as: β_1*average($AffiliatedAllocPerc$)/average($Underpricing$).

We control for several other factors that might jointly determine underpricing and affiliated allocations, such as firm size and age, and we include year fixed effects, industry fixed effects,[23] and lead underwriters fixed effects. Control variables enter the regression equation with the sign that we expect, often consistent with the existing literature. Fixed effects do not seem to have a major impact on the correlation between underpricing and our affiliated allocation measures. The reader may refer to the Web Appendix (https://tinyurl.com/webappendixnepotism) for additional details.

Overall, we find a positive and statistically significant relation between underpricing and allocations to underwriter-affiliated funds. This evidence is consistent with the nepotism hypothesis: underwriters seem to favor their affiliated funds with the allocation of underpriced shares. This positive correlation persists after controlling for issuer and issue characteristics, year and industry fixed effects, and underwriter-specific control variables. Hence, we find that fund managers' incentives, in the context of IPO allocations, seem to be more in line with those of the fund's shareholders than with those of their affiliated investment bankers. Conversely, the investment bankers' incentives seem to be more in line with those of their affiliated funds than with those of the issuer. Our evidence, based on the actual affiliated allocations reported by investment companies to the SEC, is much clearer than that available in the existing literature.

We stress that the evidence provided in this subsection does not necessarily mean that dumping-ground incentives do not exist or that they are irrelevant. It could be that dumping-ground incentives are simply weaker than nepotism incentives. There are several reasons why the nepotism conflict of interest might stand out. First, it might inherently have a greater weight in the profit function of investment banks, given the structure of the IPO market. Second, the 10(f)-3 rule might be effective in

[23]Industry fixed effects are based on the Fama-French 12-industries classification available on Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

preventing dumping-ground behavior, thus leaving space mainly for nepotism conflicts. Third, the affiliated funds might circumvent the 10(f)-3 rule by buying cold securities in the IPO aftermarket, supporting their price. This would transfer the dumping-ground conflict of interest to the secondary market, allowing us to observe mainly the nepotism conflict in the primary market. In any case, we should observe the dumping-ground conflict in the IPO allocations market whenever the benefits of dumping cold shares to affiliated funds are high enough. We explore this possibility in the next subsections, analyzing how variation in conflict of interest incentives affects the correlation between IPO allocations to affiliated funds and underpricing.

5.2. Conflict of interest incentives and the number of IPOs

Hypothesis 3 states that dumping-ground incentives are stronger when the underwriter is completing a relatively low number of deals. To test this idea, we measure the abnormal number of deals completed by each underwriter at the time the IPO in question and check whether the correlation between underpricing and affiliated allocations varies consistently with conflict of interest incentives.

For each IPO, we measure the abnormal number of IPOs completed by its underwriters as follows. Take IPO i performed in quarter q by underwriter j. We require that each underwriter j has been involved in at least one 10(f)-3 transaction in our sample. First, we define $F_{i,j,q-t}$ to be the number of IPOs filed by the underwriter j of IPO i in the quarter $q-t$. We compute $F_{i,j,q-1}$ and use it as a proxy for the number of deals that underwriter j expects to complete in quarter q. Then, we compute a benchmark measure as the average number of IPOs filed by underwriter j from quarter $q-6$ to quarter $q-3$ before the IPO i as:[24]

$$\overline{F}_{i,j} = \frac{1}{4}\sum_{t=3}^{6} F_{i,j,q-t}$$

Using this benchmark, we measure the abnormal number of IPOs that underwriter j expects to complete in quarter q as:

$$AF_{i,j} = F_{i,j,q-1} - \overline{F}_{i,j}$$

Finally, as IPO i may have more than one underwriter, we compute an aggregate measure of abnormal number of IPOs underwritten by the underwriters of IPO i as:

$$\overline{AF}_i = \frac{1}{J_i}\sum_{j=1}^{J_i} AF_{i,j}$$

where J_i is the number of underwriters of IPO i that satisfy the filter of being involved in at least one 10(f)-3 transaction in our sample.

We split the sample into terciles based on $\overline{AF}_i$. The top (bottom) tercile contains IPOs whose underwriters expect to complete a high (low) abnormal number of deals in the quarter of the IPO in question. Hypothesis 3 states that nepotism incentives dominate dumping-ground incentives in the highest tercile, while dumping-ground incentives gain importance relative to nepotism incentives in the lowest tercile. We estimate model 4 in the subsample of IPOs in the highest and lowest terciles of the variable $\overline{AF}_i$ and report the OLS regression results in Table 9. Under Hypothesis 3, we expect the coefficient β_1 to be higher in the top tercile.

[24]To compute the benchmark measure for IPOs performed in 2001 and 2002, we download additional IPO data for the period 1999-2000 from the SDC database.

[Table 9 about here.]

Consistent with Hypothesis 3, we find that the coefficient of $AffiliatedAllocPerc$ is positive and statistically significant in the highest tercile. In the lowest tercile, instead, the coefficient is much smaller in magnitude (and even negative in one specification) and is not statistically significant.

We notice that a similar qualitative pattern holds for independent funds, suggesting that unaffiliated funds are favored the most when the underwriter's need to complete deals is weakest. Changes in the magnitude and statistical significance of the coefficient of $IndependentAllocPerc$, however, are not as pronounced as they are for affiliated funds.

Even though the difference between the coefficients in the bottom and top terciles is not significant at conventional levels, we nevertheless notice that the nepotism conflict observed for the whole sample is enhanced by the highest tercile, while it is weakened by the lowest tercile. Overall, this evidence is consistent with conflict of interest incentives. When the underwriter expects to complete an abnormally low number of deals, the benefits of completing an additional IPO gain importance. This increases the incentive for dumping cold IPOs to affiliated funds, thus lowering the correlation between underpricing and affiliated allocations.

5.3. Conflict of interest incentives and commission kickbacks

Hypothesis 4a states that the correlation between underpricing and affiliated allocations should be weaker when the underwriter receives a high stream of commissions from institutional investors. Hypothesis 4b states that the correlation between underpricing and allocations to independent funds should be stronger when the underwriter receives a high stream of commissions from institutional investors.

We follow Goldstein et al. (2011) in measuring the abnormal commissions received by the brokerage arm of the lead underwriters around the IPOs' issue dates. We use the Abel Noser Solutions database to gather trade-level brokerage commission data for the period October 2000 to March 2011. We match Abel Noser's brokers to SDC's underwriters by name and require IPOs to have at least one lead underwriter matched to the Abel Noser Solutions database. Hence, for the purposes of this subsection, we drop from our sample IPOs performed in the period 2011-2013, as well as non-matched IPOs. These filters leave us with 735 IPOs in the period 2001-2010. For each IPO, we collect all trades in non-IPO stocks executed by its lead underwriters in a time window of [-60,+60] trading days around the IPO issue date and aggregate commission revenues at the daily level. We let $C_{i,j,t}$ be the dollar amount of brokerage commissions received by the lead underwriter j of IPO i in the trading day t relative to the offer date. First, we compute a benchmark level of brokerage commissions received by the lead underwriter j of IPO i as the average daily commission revenues in the non-event period [-60,-21] and [+21,+60], using this equation:

$$\overline{C}_{i,j} = \frac{1}{80}(\sum_{t=-60}^{-21} C_{i,j,t} + \sum_{t=21}^{60} C_{i,j,t})$$

Then we compute the average abnormal commission revenue in the event period [-10,-1] as:[25]

$$AC_{i,j} = \frac{1}{10}(\sum_{t=-10}^{-1} C_{i,j,t} - \overline{C}_{i,j})$$

Finally, as IPO i may have more than one lead manager, we compute an aggregate

[25]The abnormal commission revenue in the event period is positive on average and statistically different from zero (result not reported).

measure of abnormal brokerage commissions received by its underwriters as:

$$\overline{AC}_i = \sum_{j=1}^{J_i} AC_{i,j}$$

where J_i is the number of lead underwriters of IPO i matched to Abel Noser Solutions' brokers.

We split the sample into terciles based on $\overline{AC}_i$. The top (bottom) tercile contains IPOs whose underwriters received a high (low) abnormal stream of brokerage commissions from institutional trading in non-IPO stocks in the 10-day window before the IPO in question. We estimate model 4 in these two subsamples of IPOs and report our OLS regression results in Table 10. Under Hypotheses 3a and 3b, we expect the coefficient β_1 to be higher in the bottom tercile and the coefficient β_2 to be higher in the top tercile.

[Table 10 about here.]

Consistent with Hypothesis 4a, we observe that the coefficient of $AffiliatedAllocPerc$ is lower in magnitude when the lead underwriters receive an abnormally high stream of brokerage commissions from institutional investors. Statistical significance is also weaker in the highest tercile of $\overline{AC}_i$. Consistent with Hypothesis 4b, the coefficient of $IndependentAllocPerc$ is higher when quid-pro-quo incentives are likely at play. Moreover, the coefficient is not statistically different from zero when institutional investors do not pay high brokerage commissions to the lead underwriters. This finding provides additional evidence of the importance of commission paybacks in the IPO allocation process, supporting Reuter (2006), Nimalendran et al. (2007), Goldstein et al. (2011), and Jenkinson et al. (2018).

Even though the differences between the coefficients in the bottom and top terciles are not significant at conventional levels, we nevertheless notice that the nepotism conflict (the commission-kickbacks conflict) observed for the whole sample is enhanced (weakened) by the lowest tercile. Overall, this evidence is consistent with underwriters' conflict of interest incentives. When brokerage commissions gain weight in the profit function of the investment bank, the revenues from allocating underpriced shares to the affiliated investment management arm become less important and the underwriter tends to favor non-affiliated institutions that have entered into a quid-pro-quo agreement.

5.4. Conflict of interest incentives and information asymmetry

Hypothesis 5a states that the correlation between underpricing and affiliated allocations should be stronger for firms with low information asymmetry. Hypothesis 5b states that the correlation between underpricing and unaffiliated, independent allocations should be stronger for firms with high information asymmetry.

As our proxy for information asymmetry we use the size of the firm, $ln(Assets)$, and split the sample into terciles based on firm size. We estimate model 4 in the highest and lowest terciles and report our OLS regression results in Table 11. Under Hypotheses 5a and 5b, we expect the coefficient β_1 to be higher in the top tercile and the coefficient β_2 to be higher in the bottom tercile.

[Table 11 about here.]

Consistent with Hypothesis 5a, we observe that the coefficient of $AffiliatedAllocPerc$ is positive and statistically significant in the highest tercile, while it is statistically not different from zero in the lowest tercile. Moreover, in two specifications, the sign of the coefficient becomes negative. There is some evidence in favor of Hypothesis 5b as well, though it is weaker: the magnitude and statistical significance of the coefficient of $IndependentAllocPerc$ are higher in the lowest tercile of $ln(Assets)$.

Even though the difference between the coefficients in the bottom and top terciles is not significant at conventional levels, we nevertheless notice that the nepotism conflict observed for the whole sample is driven by the highest tercile, while it is weakened by the lowest tercile. Overall, this evidence is consistent with underwriters' conflict of interest incentives and with standard information production theories of bookbuilding. When information asymmetry is high, the underwriter tends to favor those investors whose indications of interest in the bookbuilding process are more valuable. When information asymmetry is low, price discovery is less important and the nepotism conflict emerges.

6. Conclusion

We identify an unexplored conflict of interest in IPOs, and we argue that it may contribute to IPO underpricing. We hypothesize that underwriting banks may underprice IPOs to benefit their affiliated funds (the supernepotism hypothesis). Using the 10(f)-3 rule of the Investment Company Act, we construct a hand-collected dataset of IPO allocations received by funds affiliated to the underwriter. To assess the causal effect of affiliated on the IPO offer price, we implement a fuzzy regression discontinuity design. We exploit a regulatory threshold, set by section 10(f)-3 of the Investment Company Act, which provides exogenous variation in the allocation decision. We find that a one percentage point increase in the allocations to affiliated funds causes underpricing to be nearly 5.4 percentage points higher. Our evidence suggests that the supernepotism conflict of interest has real costs for the issuing firm.

Our findings shed light on a previously unexplored tradeoff facing IPO issuers. For them, the benefits of going public must be compared with the potential foregone IPO proceeds stemming from underpricing on the part of the IPO underwriter. Our conversations with asset managers suggest to us that the supernepotism behavior we document, and its consequences for IPO pricing, are known to some participants in the

IPO market. It is not clear to us whether this behavior is widely known to potential IPO issuers. Conceivably, an IPO issuer concerned about supernepotism could turn to an underwriter less active in the fund management business, but we have no indication, even anecdotal, that this is the case. An intriguing possibility is that issuers may view the underwriter's dumping ground incentives as an offsetting virtue to supernepotism: an issuer might accept the risk of foregone proceeds due to supernepotism, if that risk comes bundled with the guarantee that the underwriter will use his own funds to place the issuer's shares and guarantee a successful offering when market conditions deteriorate.

Our hand-collected dataset of affiliated IPO allocations also enables us to revisit the dumping-ground and nepotism hypotheses analyzed in the prior literature. We find that, controlling for other joint determinants, there is a strong and statistically significant positive correlation between underpricing and affiliated allocations: a one percentage point increase in the allocation to affiliated funds is associated with a 0.62 percentage point increase in underpricing. This evidence suggests that the nepotism conflict is more pervasive than the dumping-ground one. Our evidence supporting the nepotism hypothesis is much clearer than that reported in previous papers.

We also document that the correlation between affiliated allocations and underpricing varies consistently with the nepotism and dumping-ground incentives. The positive correlation between affiliated allocations and underpricing is weaker in periods when the underwriter performs an abnormally low number of IPOs. This finding is consistent with the idea that, in such periods, dumping-ground incentives gain importance relative to those of nepotism, as the marginal benefit of completing an IPO is higher for the underwriter. Moreover, we find that the positive correlation between affiliated allocations and underpricing is weaker when the investment bank underwriting the IPO receives an abnormally high stream of brokerage commissions from other non-affiliated funds. In this scenario, underwriters tend to favor the clients that give them commission kickbacks, and nepotism incentives become less important. Finally, we find some evidence consistent with both information-based bookbuilding theories and conflict of interest incentives. The positive correlation between affiliated allocations and underpricing is stronger when the information asymmetry about the issuer is lower. In these IPOs, the information providing role of the bookbuilding method is not as important as it is for IPOs whose value is more uncertain. Hence, underwriters do not need to reward independent funds for their information-revealing indications of interest and the nepotism conflict emerges.

One interesting question that remains unanswered is why the nepotism conflict dominates the dumping-ground one in the context of IPO allocations. We argue that there are several reasons why the nepotism conflict might stand out. First, it might inherently have a greater weight in the profit function of investment banks, given the structure of the IPO market. Second, the 10(f)-3 rule might be an effective tool preventing dumping-ground behavior, thus leaving space mainly for nepotism conflicts. Third, affiliated funds might circumvent the 10(f)-3 rule by buying cold securities in the IPO aftermarket, supporting their price. Such behavior would transfer the dumping-ground conflict to the secondary market, allowing us to observe mainly the nepotism conflict in the primary market.

Overall, we find that the funds affiliated to banks involved in underwriting an IPO receive two benefits: (1) underwriters underprice IPOs more when they expect their affiliated funds to received IPO shares; (2) underwriters allocate more underpriced shares to their affiliated funds. The first channel has not so far received attention, and points to a direct monetary cost for IPO issuers of the conflict of interest faced by banks involved in both IPO underwriting and asset management.

Table 1
List of variables.
This table lists and defines all the variables used in this paper.

Variable	Description
IPO VARIABLES	
Underpricing	(first day closing price - offer price)*100/offer price
Age	age of the issuer in years computed as: issue year - founding year
Proceeds	total proceeds from the issue in millions of dollars
Assets	total assets before the IPO in millions of dollars
Adjustment	(offer price - midpoint)*100/midpoint, where "midpoint" is the original midpoint of the filing range
OnlyPrimaryShares	dummy variable equal to one if all the shares issued are primary shares
Nasdaq	dummy variable equal to one if the IPO is listed on the NASDAQ
Foreign	dummy variable equal to one if the issuer is located outside the United States
VentureCapitalBack	dummy variable equal to one if the IPO is backed by a venture capitalist
LengthIPOprocess	length of the IPO process in months computed as: (issue date - filing date)/30.4375
HighRankDummy	dummy variable equal to one if at least one underwriter has a Ritter ranking equal to 9
NumberLeadManagers	number of bookrunners and lead managers in the syndicate
NumberSyndicateMembers	total number of syndicate members
GrossSpread	gross underwriters' spread
FirmCommitment	dummy variable equal to one if the securities are issued under a firm-commitment contract
ALLOCATION VARIABLES	
AffiliatedAllocPerc	percentage of the issue allocated to affiliated funds
AffiliatedAllocDummy	dummy variable equal to one if affiliated funds receive shares in the IPO
IndependentAllocPerc	percentage of the issue held by s12 funds at the first reporting date after the IPO minus AffiliatedAllocPerc
OTHER VARIABLES	
$\overline{AF}$	Abnormal number of deals that the lead managers expect to complete in the quarter of the IPO
$\overline{AC}$	Abnormal stream of brokerage commissions to the lead underwriters in a 10-day window before the IPO

Table 2

Summary statistics of IPO data.

This table provides summary statistics at the issuer level for 1,086 eligible IPOs (Panel A) and 208 non-eligible IPOs (Panel B). We define an IPO as "eligible" if it satisfies these conditions: the issuer is at least three years old; the securities are issued under a firm-commitment contract; there is more than one underwriter in the syndicate; at least one lead underwriter has been involved in a 10(f)-3 transaction in our sample. IPO variables are defined in Table 1. For each variable, the table reports its average (mean), its median (p50), and its standard deviation (sd).

(A) Eligible IPOs

	mean	p50	sd
Underpricing	14.2	9.09	19.4
Age	22.9	11	27.7
Proceeds	219	117	266
Assets	1351	218	2373
Adjustment	-1.59	0	13.3
GrossSpread	6.63	7	0.73
NumberLeadManagers	2.38	2	1.47
NumberSyndicateMembers	7.51	6	4.59
LengthIPOprocess	4.41	3.37	3.57
OnlyPrimaryShares	0.52	1	0.50
Nasdaq	0.61	1	0.49
Foreign	0.097	0	0.30
VentureCapitalBack	0.45	0	0.50
HighRankDummy	0.78	1	0.41

(B) Non-eligible IPOs

	mean	p50	sd
Underpricing	5.13	1.16	13.9
Age	11.1	5	22.5
Proceeds	86.7	48.2	112
Assets	1123	51.3	2455
Adjustment	-4.49	0	11.2
GrossSpread	6.93	7	0.66
NumberLeadManagers	1.69	1	1.13
NumberSyndicateMembers	4.80	4	3.34
LengthIPOprocess	4.39	3.60	3.39
OnlyPrimaryShares	0.79	1	0.41
Nasdaq	0.75	1	0.43
Foreign	0.21	0	0.41
VentureCapitalBack	0.31	0	0.46
HighRankDummy	0.25	0	0.44

Table 3

Summary statistics of allocation data.

This table summarizes the allocation data at the issuer level for 1,086 eligible IPOs (Panel A) and 208 non-eligible IPOs (Panel B). $AffiliatedAllocPerc$ is the percentage allocated to funds affiliated with the underwriters; $AffiliatedAllocDummy$ is a dummy variable identifying IPOs with at least one share allocated to affiliated funds; and $IndependentAllocPerc$ is the percentage allocated to funds that are not affiliated with the underwriters.

(A) Eligible IPOs

	mean	p50	sd
AffiliatedAllocPerc	1.44	0.12	2.36
AffiliatedAllocDummy	0.56	1	0.50
IndependentAllocPerc	18.3	16.1	13.3

(B) Non-eligible IPOs

	mean	p50	sd
AffiliatedAllocPerc	0.077	0	0.68
AffiliatedAllocDummy	0.082	0	0.27
IndependentAllocPerc	10.1	5.73	12.0

Table 4
The effect of affiliated allocations on underpricing - fuzzy RDD estimates.
This table contains the second stage coefficients of a local 2SLS regression of $Underpricing$ on two measures of affiliated allocations instrumented by z, for different values of the bandwidth h. The two measures are $AffiliatedAllocPerc$ (Panel A) and $AffiliatedAllocDummy$ (Panel B). z is a dummy variable equal to one if $Age \geq 3$ and zero otherwise, $x = Age - 3$, and $z\_x = z \cdot x$. Relevant statistics from the first stage regression (F, coefficient of z, t-stat of z, and R^2) are also reported. All percentages and returns are multiplied by 100. All non-dummy variables except Age are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

(A)

	(1) h=1	(2) h=2	(3) h=2	(4) h=3	(5) h=3	(6) h=3
AffiliatedAllocPerc	6.72**	8.76***	5.28	10.4***	6.55*	5.43*
	(2.22)	(3.12)	(1.29)	(3.59)	(1.74)	(1.90)
x			2.17		1.40	2.67*
			(0.79)		(1.02)	(1.67)
z_x						-2.16
						(-0.70)
Constant	4.47***	3.73*	7.15*	1.49	5.01	7.64***
	(2.67)	(1.90)	(1.76)	(0.58)	(1.48)	(2.67)
F (2nd stage)	4.93	9.76	6.47	12.9	9.76	7.23
F (1st stage)	10.0	24.6	12.2	23.0	12.8	14.4
Coefficient of z (1st stage)	1.53	1.28	1.79	1.13	1.59	1.64
t-stat of z (1st stage)	3.16	4.96	2.18	4.79	2.68	3.30
R^2 (1st stage)	0.14	0.097	0.10	0.064	0.067	0.067
Observations	57	130	130	217	217	217

(B)

	(1) h=1	(2) h=2	(3) h=2	(4) h=3	(5) h=3	(6) h=3
AffiliatedAllocDummy	24.6**	28.5***	21.1	27.4***	29.0**	24.8**
	(2.66)	(3.62)	(1.47)	(5.12)	(2.00)	(2.17)
x			1.42		-0.22	1.09
			(0.48)		(-0.12)	(0.68)
z_x						-1.83
						(-0.73)
Constant	1.72	0.91	3.88	0.51	-0.097	2.87
	(0.74)	(0.33)	(0.69)	(0.24)	(-0.02)	(0.69)
F (2nd stage)	7.05	13.1	7.82	26.3	12.7	9.11
F (1st stage)	13.1	28.0	13.9	55.6	28.2	18.9
Coefficient of z (1st stage)	0.42	0.39	0.45	0.43	0.36	0.36
t-stat of z (1st stage)	3.63	5.29	2.41	7.46	2.62	2.71
R^2 (1st stage)	0.19	0.15	0.15	0.16	0.16	0.16
Observations	57	130	130	217	217	217

Table 5

Reduced-form regression.

This table contains coefficients of the reduced-form regression of *Underpricing* on z, x, and z_x, for different values of the bandwidth h. z is a dummy variable equal to one if $Age \geq 3$ and zero otherwise, $x = Age - 3$, and $z\_x = z \cdot x$. All percentages and returns are multiplied by 100. All non-dummy variables except *Age* are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	(1) h=1	(2) h=2	(3) h=2	(4) h=3	(5) h=3	(6) h=3
z	10.3***	11.2***	9.45	11.8***	10.4**	8.90**
	(2.79)	(3.78)	(1.49)	(5.24)	(2.14)	(2.17)
x			0.86		0.44	1.65
			(0.27)		(0.30)	(1.20)
z_x						-1.83
						(-0.74)
Constant	5.36***	4.63**	5.84	3.88***	4.70	6.97**
	(3.08)	(2.46)	(1.31)	(2.64)	(1.55)	(2.46)
F	7.77	14.3	7.61	27.5	13.7	9.43
R^2	0.12	0.078	0.079	0.078	0.078	0.079
Observations	57	130	130	217	217	217

Table 6
Fuzzy RDD in a subsample of IPOs whose exact age is known.
This table contains the second stage coefficients of a local 2SLS regression of $Underpricing$ on two measures of affiliated allocations instrumented by z, for a bandwidth $h = 1$, in a subsample of 33 IPOs whose exact age is known. The two measures are $AffiliatedAllocPerc$ (Panel A) and $AffiliatedAllocDummy$ (Panel B). z is a dummy variable equal to one if $Age \geq 3$ and zero otherwise, $x = Age - 3$, and $z\_x = z \cdot x$. Relevant statistics from the first stage regression (F, coefficient of z, t-stat of z, and R^2) are also reported. All percentages and returns are multiplied by 100. All non-dummy variables except Age are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

(A)

	(1)	(2)	(3)
AffiliatedAllocPerc	5.44*	3.63	3.63
	(1.72)	(0.81)	(0.68)
x		3.87	3.85
		(0.47)	(0.21)
z_x			0.027
			(0.00)
Constant	7.65**	9.81*	9.80
	(2.05)	(1.78)	(0.77)
F (2nd stage)	2.96	1.66	1.46
F (1st stage)	10.8	6.46	4.97
Coefficient of z (1st stage)	2.08	4.03	2.98
t-stat of z (1st stage)	3.29	1.76	2.05
R^2 (1st stage)	0.15	0.20	0.21
Observations	33	33	33

(B)

	(1)	(2)	(3)
AffiliatedAllocDummy	24.9*	38.2	43.0
	(1.97)	(0.90)	(0.68)
x		-6.18	-10.4
		(-0.36)	(-0.29)
z_x			4.41
			(0.13)
Constant	5.70	1.20	-1.50
	(1.30)	(0.08)	(-0.05)
F (2nd stage)	3.88	1.48	1.35
F (1st stage)	10.3	5.18	7.21
Coefficient of z (1st stage)	0.45	0.38	0.25
t-stat of z (1st stage)	3.21	1.14	0.73
R^2 (1st stage)	0.19	0.19	0.20
Observations	33	33	33

Table 7

Fuzzy RDD using only lead underwriters' affiliated allocations.

This table contains the second stage coefficients of a local 2SLS regression of $Underpricing$ on two measures of lead managers' affiliated allocations instrumented by z, for different values of the bandwidth h. The two measures are $AffiliatedAllocPerc$ (Panel A) and $AffiliatedAllocDummy$ (Panel B). z is a dummy variable equal to one if $Age \geq 3$ and zero otherwise, $x = Age - 3$, and $z\_x = z \cdot x$. Relevant statistics from the first stage regression (F, coefficient of z, t-stat of z, and R^2) are also reported. All percentages and returns are multiplied by 100. All non-dummy variables except Age are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

(A)

	(1) h=1	(2) h=2	(3) h=2	(4) h=3	(5) h=3	(6) h=3
AffiliatedAllocPerc	10.9**	15.3***	8.11	20.1***	9.94*	8.53*
	(2.17)	(2.80)	(1.31)	(2.90)	(1.73)	(1.83)
x			2.56		1.91	2.88*
			(1.00)		(1.63)	(1.70)
z_x						-1.79
						(-0.57)
Constant	4.63***	3.74*	7.77**	0.85	5.96**	8.01***
	(2.67)	(1.87)	(2.09)	(0.25)	(2.06)	(2.72)
F (2nd stage)	4.69	7.84	6.28	8.41	9.17	6.81
F (1st stage)	7.18	14.9	7.42	11.6	7.14	8.29
Coefficient of z (1st stage)	0.95	0.74	1.17	0.58	1.05	1.04
t-stat of z (1st stage)	2.68	3.86	1.94	3.41	2.42	2.87
R^2 (1st stage)	0.11	0.061	0.066	0.034	0.040	0.040
Observations	57	130	130	217	217	217

(B)

	(1) h=1	(2) h=2	(3) h=2	(4) h=3	(5) h=3	(6) h=3
AffiliatedAllocDummy	28.9***	35.3***	23.7	37.3***	30.2**	27.3**
	(2.72)	(3.59)	(1.54)	(4.68)	(2.07)	(2.17)
x			1.80		0.72	1.49
			(0.69)		(0.51)	(0.95)
z_x						-1.21
						(-0.47)
Constant	2.15	1.56	5.11	0.44	2.44	4.15
	(0.92)	(0.59)	(1.10)	(0.19)	(0.59)	(1.09)
F (2nd stage)	7.39	12.9	8.25	21.9	12.7	8.90
F (1st stage)	10.2	21.6	10.7	34.3	17.1	11.4
Coefficient of z (1st stage)	0.36	0.32	0.40	0.32	0.34	0.33
t-stat of z (1st stage)	3.19	4.65	2.21	5.86	2.59	2.63
R^2 (1st stage)	0.15	0.11	0.11	0.097	0.097	0.098
Observations	57	130	130	217	217	217

Table 8

OLS regression of underpricing on affiliated allocations.

This table contains the coefficient estimates from several specifications of an OLS regression of *Underpricing* on two measures of affiliated allocations: a dummy variable that identifies IPOs with affiliated allocations (columns 1-5) and the percentage of the issue allocated to affiliated funds (columns 6-10). The sample includes 1086 eligible IPOs in the period 2001-2013. Columns 2, 3, 7 and 8 introduce IPO level control variables, as defined in section 3. Columns 4 and 9 introduce year and industry fixed effects. Columns 5 and 10 introduce lead underwriters' control variables. All percentages and returns are multiplied by 100. All non-dummy variables except *Age* are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AffiliatedAllocDummy	11.0***	6.94***	6.54***	6.28***	6.50***					
	(10.30)	(6.11)	(5.45)	(5.15)	(5.15)					
AffiliatedAllocPerc						0.99***	0.81***	0.70***	0.62**	0.67**
						(3.48)	(3.31)	(2.80)	(2.44)	(2.52)
IndependentAllocPerc	0.30***	0.21***	0.19***	0.18***	0.17***	0.34***	0.23***	0.21***	0.19***	0.17***
	(6.50)	(5.18)	(4.71)	(4.44)	(3.93)	(7.21)	(5.55)	(4.98)	(4.59)	(4.03)
ln(Age+1)		-1.64***	-1.13*	-1.70***	-1.60**		-1.65***	-1.08*	-1.61**	-1.48**
		(-2.86)	(-1.91)	(-2.64)	(-2.44)		(-2.88)	(-1.83)	(-2.51)	(-2.25)
ln(Assets)		-1.55***	-0.68	-0.94	-0.90		-1.45***	-0.78	-1.06	-1.07
		(-3.91)	(-1.10)	(-1.43)	(-1.30)		(-3.54)	(-1.26)	(-1.60)	(-1.54)
Adjustment		0.63***	0.62***	0.57***	0.56***		0.70***	0.67***	0.63***	0.61***
		(15.91)	(14.12)	(12.70)	(11.92)		(18.46)	(15.95)	(14.38)	(13.60)
OnlyPrimaryShares		-0.91	-1.23	-0.32	-0.33		-1.59	-1.76*	-0.79	-0.80
		(-0.93)	(-1.26)	(-0.31)	(-0.31)		(-1.62)	(-1.80)	(-0.78)	(-0.75)
Nasdaq		1.43	1.17	1.85	2.05		0.38	0.43	1.21	1.39
		(1.09)	(0.89)	(1.42)	(1.51)		(0.30)	(0.33)	(0.94)	(1.04)
Foreign		0.88	0.17	-0.080	-0.034		1.07	0.29	-0.0047	0.11
		(0.54)	(0.11)	(-0.05)	(-0.02)		(0.64)	(0.17)	(-0.00)	(0.06)
ln(Proceeds)			-0.33	0.45	0.27			0.28	1.15	0.91
			(-0.23)	(0.31)	(0.17)			(0.20)	(0.79)	(0.58)
VentureCapitalBack			3.52**	4.98***	5.19***			3.49**	4.98***	5.20***
			(2.49)	(3.48)	(3.44)			(2.47)	(3.49)	(3.45)
LengthIPOprocess			-0.39***	-0.28**	-0.29**			-0.38***	-0.27**	-0.28**
			(-3.09)	(-2.19)	(-2.21)			(-2.96)	(-2.09)	(-2.10)
HighRankDummy			0.87	1.11	2.01			2.01	2.29*	2.89*
			(0.66)	(0.82)	(1.17)			(1.51)	(1.68)	(1.68)
NumberLeadManagers			0.40	-0.34	1.89			0.38	-0.33	1.48
			(1.02)	(-0.73)	(1.26)			(0.95)	(-0.71)	(0.98)
NumberSyndicateMembers			-0.028	0.12	0.10			0.0067	0.12	0.11
			(-0.22)	(0.77)	(0.63)			(0.05)	(0.75)	(0.66)
GrossSpread			1.65*	1.74*	1.61			2.17**	2.20**	2.08*
			(1.71)	(1.77)	(1.43)			(2.27)	(2.26)	(1.89)
Constant	2.63***	19.8***	3.97	8.67	9.33	6.66***	22.8***	0.057	5.26	6.49
	(2.81)	(6.36)	(0.38)	(0.78)	(0.73)	(6.67)	(7.27)	(0.01)	(0.48)	(0.52)
industry FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
year FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
underwriter FE	No	No	No	No	Yes	No	No	No	No	Yes
R^2	0.131	0.342	0.354	0.393	0.408	0.067	0.328	0.343	0.383	0.397
F	86.7	64.8	36.4	16.7	9.99	32.4	60.9	34.4	15.9	9.47
Observations	1086	1086	1086	1086	1086	1086	1086	1086	1086	1086

Table 9
OLS regression by number of IPOs completed by the underwriters.
This table contains the coefficient estimates from several specifications of an OLS regression of *Underpricing* on its determinants in two subsamples. For each IPO, we compute a measure of the abnormal number of IPOs completed by its underwriters. We split the sample into terciles based on this measure. Regression results are reported for the top tercile ("High") and the bottom tercile ("Low"). The sample includes IPOs performed in the period 2001-2013. All percentages and returns are multiplied by 100. All non-dummy variables except *Age* are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	Low number of IPOs			High number of IPOs		
	(1)	(2)	(3)	(4)	(5)	(6)
AffiliatedAllocPerc	0.32	0.15	-0.15	1.20**	0.87**	1.08**
	(0.69)	(0.33)	(-0.31)	(2.33)	(2.14)	(2.39)
IndependentAllocPerc	0.32***	0.19***	0.17**	0.42***	0.30***	0.23***
	(4.26)	(2.97)	(2.51)	(4.82)	(4.09)	(2.89)
IPO controls	No	Yes	Yes	No	Yes	Yes
industry FE	No	No	Yes	No	No	Yes
year FE	No	No	Yes	No	No	Yes
underwriter FE	No	No	Yes	No	No	Yes
R^2	0.054	0.357	0.456	0.087	0.381	0.469
F	9.46	13.6	5.90	13.7	13.3	5.91
Observations	362	362	362	362	362	362

Table 10

OLS regression by brokerage commissions received by the underwriters.

This table contains the coefficient estimates from several specifications of an OLS regression of *Underpricing* on its determinants in two subsamples. For each IPO, we compute a measure of abnormal brokerage commissions received by its underwriters from institutional investors in a 10-day window before the IPO. We split the sample into terciles based on this measure. Regression results are reported for the top tercile ("High") and the bottom tercile ("Low"). The sample includes IPOs performed in the sub-period 2001-2010. All percentages and returns are multiplied by 100. All non-dummy variables except *Age* are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	Low commissions from institutional investors			High commissions from institutional investors		
	(1)	(2)	(3)	(4)	(5)	(6)
AffiliatedAllocPerc	2.10***	1.45**	1.71**	0.90**	0.62*	0.79*
	(3.11)	(2.04)	(2.30)	(1.99)	(1.67)	(1.95)
IndependentAllocPerc	0.080	0.027	0.088	0.26**	0.25***	0.29***
	(0.84)	(0.35)	(1.05)	(2.56)	(2.82)	(2.95)
IPO controls	No	Yes	Yes	No	Yes	Yes
industry FE	No	No	Yes	No	No	Yes
year FE	No	No	Yes	No	No	Yes
underwriter FE	No	No	Yes	No	No	Yes
R^2	0.053	0.425	0.499	0.038	0.349	0.445
F	5.31	10.4	5.13	4.85	8.59	3.98
Observations	246	246	246	245	245	245

Table 11
OLS regression by firm size.
This table contains the coefficient estimates from several specifications of an OLS regression of *Underpricing* on its determinants in two subsamples. We split the sample into terciles based on $ln(Assets)$. Regression results are reported for the top tercile ("Large") and the bottom tercile ("Small"). The sample includes IPOs performed in the period 2001-2013. All percentages and returns are multiplied by 100. All non-dummy variables except *Age* are winsorized at the 95% level. Heteroschedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	Small firm size			Large firm size		
	(1)	(2)	(3)	(4)	(5)	(6)
AffiliatedAllocPerc	1.15	-0.21	-0.22	1.12***	0.86***	0.73**
	(1.59)	(-0.39)	(-0.36)	(3.35)	(2.86)	(2.27)
IndependentAllocPerc	0.35***	0.18***	0.17*	0.17**	0.13**	0.051
	(4.14)	(2.65)	(1.95)	(2.34)	(2.02)	(0.70)
IPO controls	No	Yes	Yes	No	Yes	Yes
industry FE	No	No	Yes	No	No	Yes
year FE	No	No	Yes	No	No	Yes
underwriter FE	No	No	Yes	No	No	Yes
R^2	0.058	0.389	0.486	0.056	0.336	0.403
F	10.7	15.5	7.70	8.97	11.9	4.48
Observations	362	362	362	362	362	362

Fig. 1. Number of IPOs by year. This figure shows the number of eligible and non-eligible IPOs by yea.r

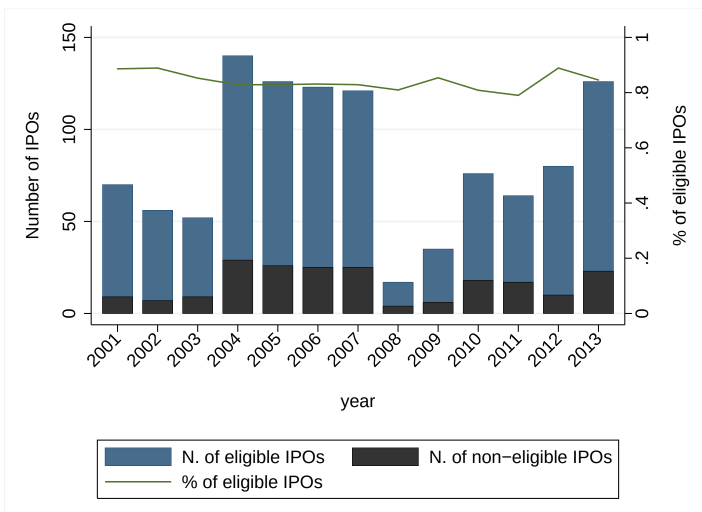
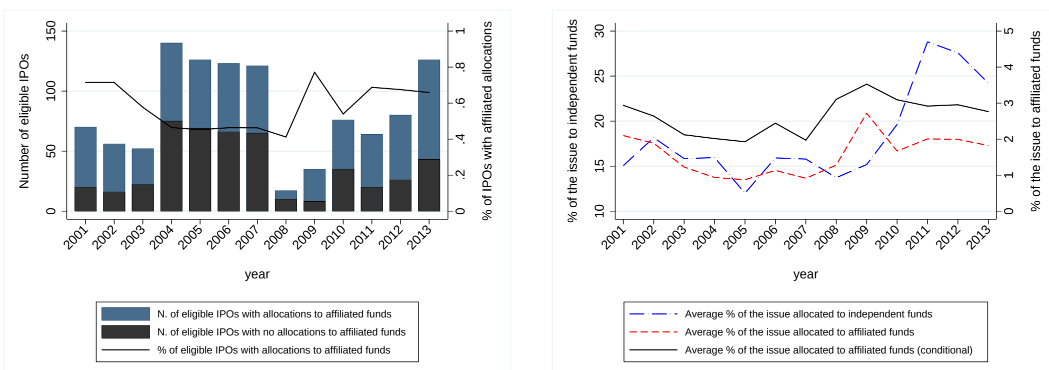


Fig. 2. Institutional IPO allocations by year. This figure shows the affiliated and independent allocations from 2001 to 2013 of 1,086 eligible IPOs. Panel (A) plots the number and the percentage of IPOs that involve at least one affiliated transaction, and the number of IPOs with no affiliated allocations. Panel (B) plots the average percentage of the issue allocated to affiliated funds, the average percentage of the issue allocated to independent funds, and the average percentage of the issue allocated to affiliated funds conditional on IPOs involving at least one affiliated transaction.



(A) (B)

Fig. 3. Identification strategy. This figure visualizes an intuitive representation of our identification strategy.

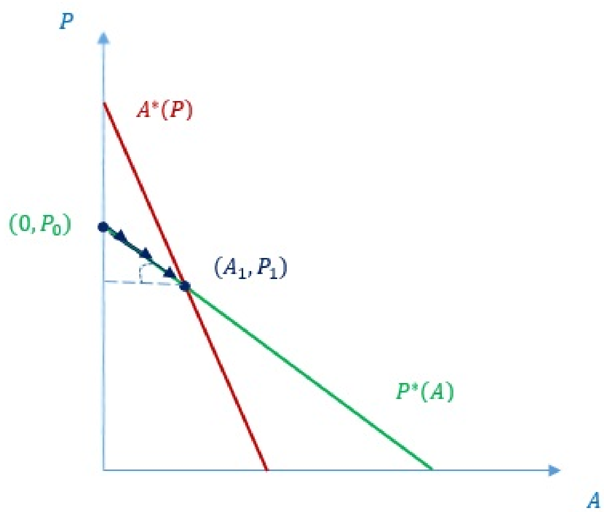
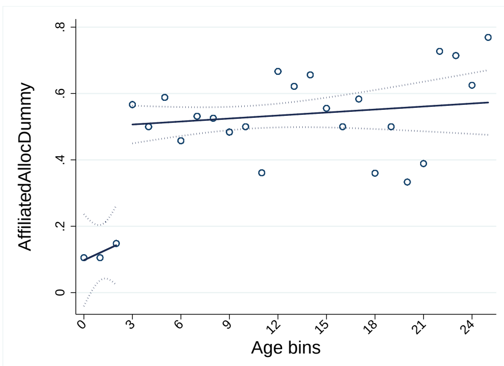
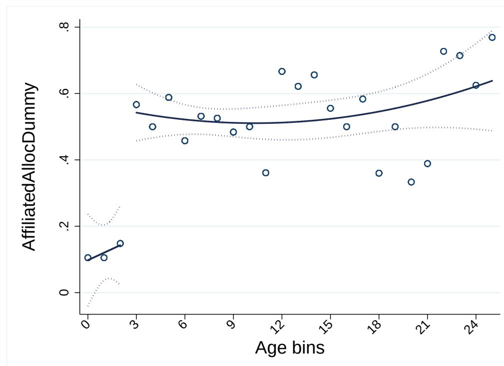


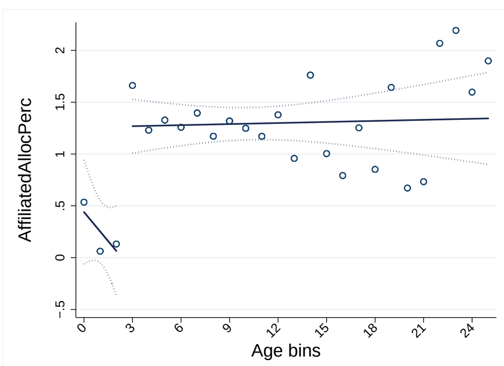
Fig. 4. Affiliated allocations by age. This figure plots average treatments by forcing variable. We compute the average $AffiliatedAllocDummy$ (Panel A and B) and $AffiliatedAllocPerc$ (Panel C and D) for each age group (bin) of one-year size. Fitted values come from a linear fit on both sides of the three-year cutoff in panels (A) and (C); they come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$ in panels (B) and (D). 95% confidence intervals are reported with dotted lines.



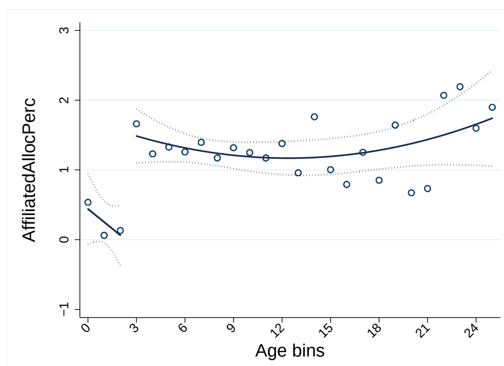
(A)



(B)

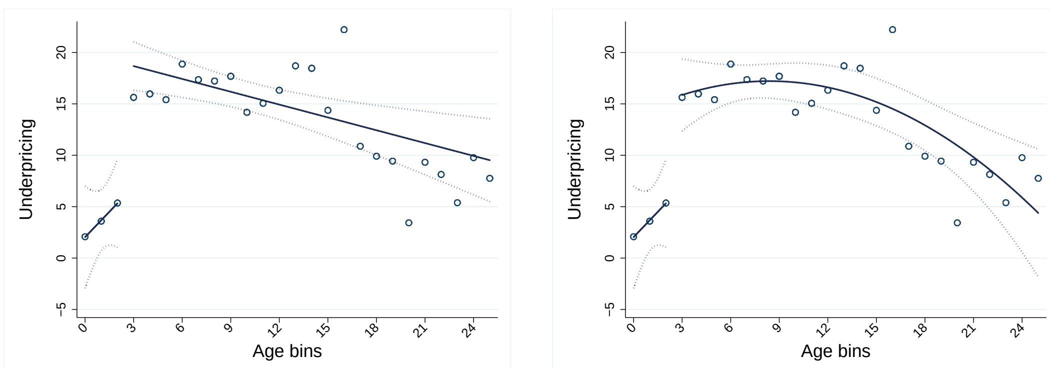


(C)



(D)

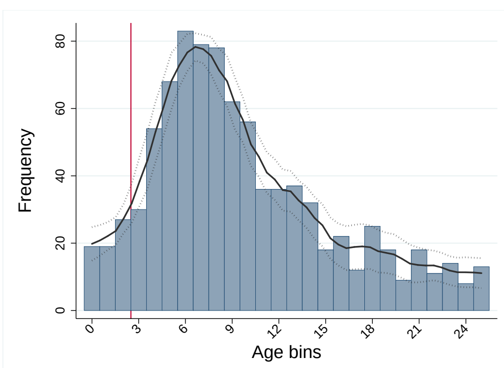
Fig. 5. Underpricing by age. This figure plots the average outcome by forcing variable. We compute average *Underpricing* for each age group (bin) of one-year size. Fitted values come from a linear fit on both sides of the three-year cutoff in panel (A); they come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$ in panel (B). 95% confidence intervals are reported with dotted lines.



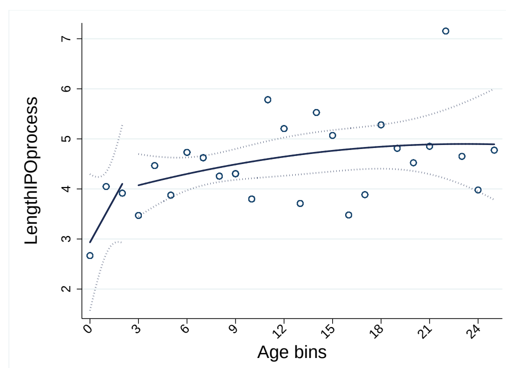
(A)

(B)

Fig. 6. Density and IPO process' length by age. This figure plots the number of IPOs (Panel A) and the average length of the IPO process (Panel B) by forcing variable. Panel (A) reports the histogram and its smoothed values from a kernel-weighted polynomial regression with Epanechnikov kernel. In Panel (B), we compute average $LengthIPOprocess$ for each age group (bin) of one-year size. Fitted values come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$. 95% confidence intervals are reported with dotted lines.



(A)



(B)

Fig. 7. Density by age for each underwriter. This figure plots the number of IPOs underwritten by the most important underwriters by age groups (bins) of one-year size. All sub-figures report histograms and smoothed values from kernel-weighted polynomial regressions with Epanechnikov kernel. 95% confidence intervals are reported with dotted lines.

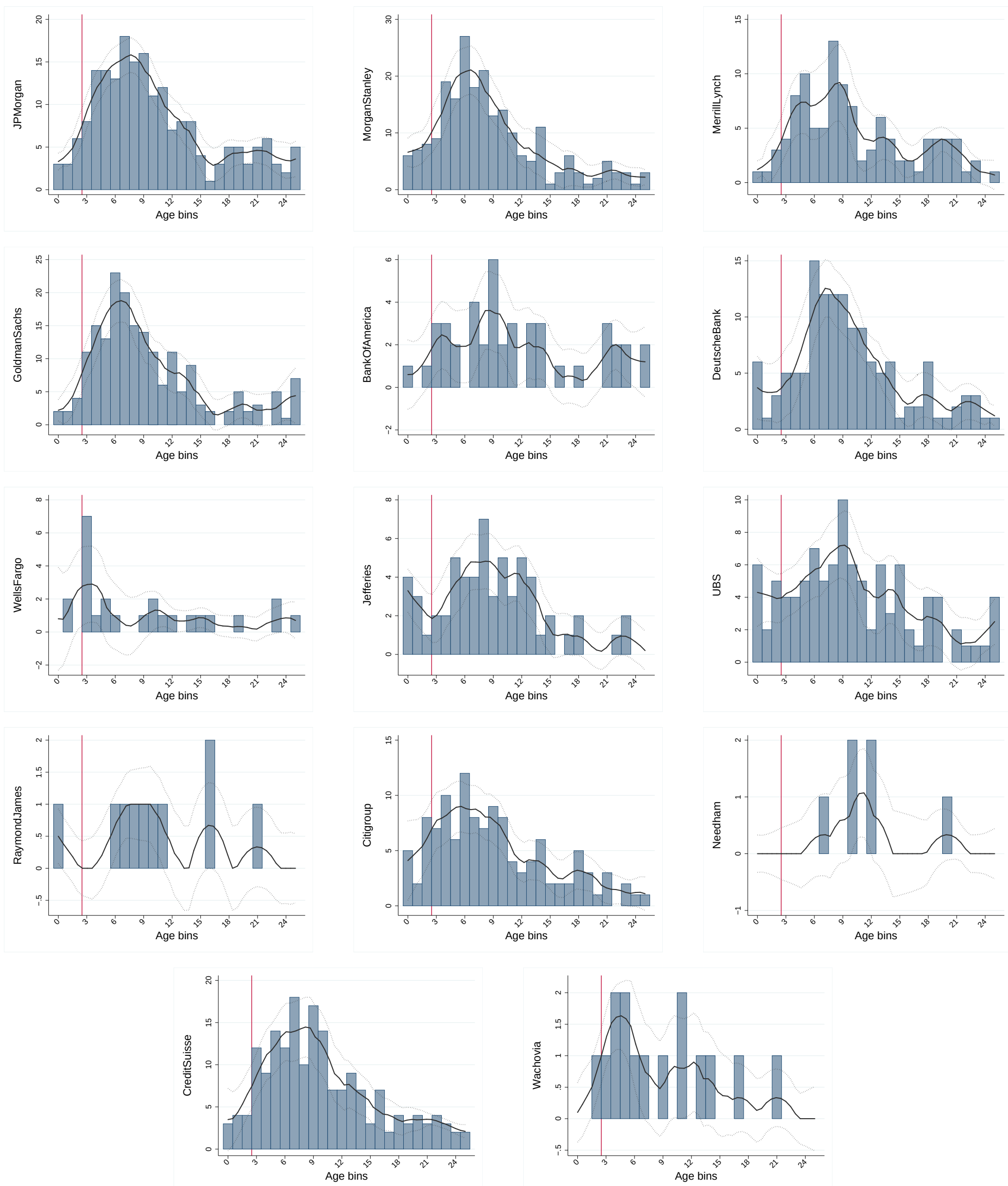


Fig. 8. Covariates by age. This figure plots average covariates by forcing variable. We compute the average value of each control variable by age groups (bins) of one-year size. Fitted values come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$. 95% confidence intervals are reported with dotted lines.

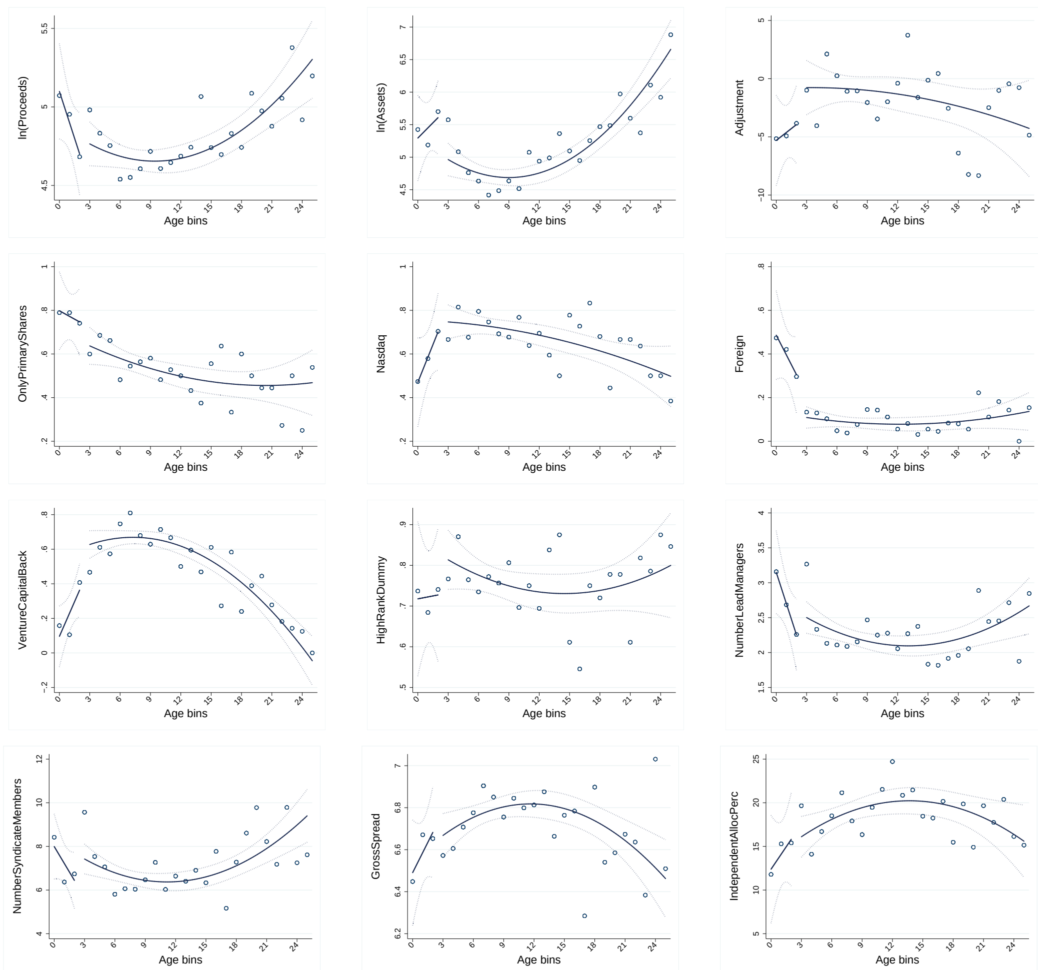
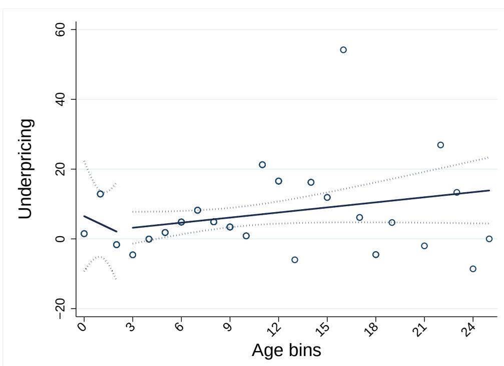
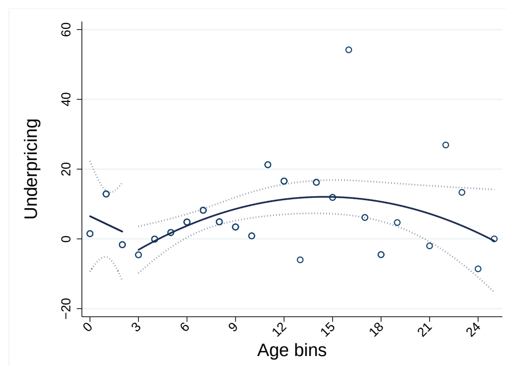


Fig. 9. Underpricing by age for non-eligible IPOs. This figure plots the average outcome by forcing variable for non-eligible IPOs. We compute average *Underpricing* for each age group (bin) of one-year size. Fitted values come from a linear fit on both sides of the three-year cutoff in panel (A); they come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$ in panel (B). 95% confidence intervals are reported with dotted lines.

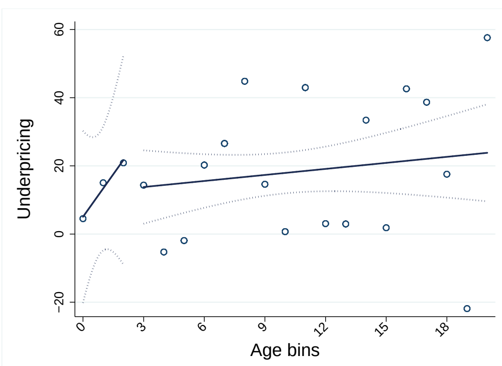


(A)

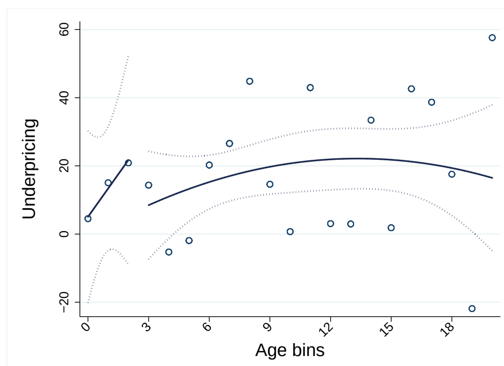


(B)

Fig. 10. Underpricing by age for European IPOs. This figure plots the average outcome by forcing variable for a sample of 488 European IPOs performed in the period 2001-2013. We compute average *Underpricing* for each age group (bin) of one-year size. Fitted values come from a linear fit on both sides of the three-year cutoff in panel (A); they come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$ in panel (B). 95% confidence intervals are reported with dotted lines.

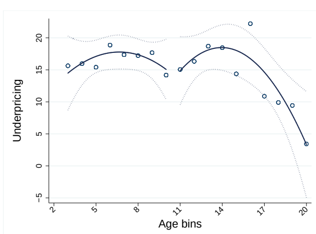


(A)

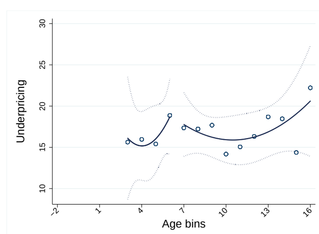


(B)

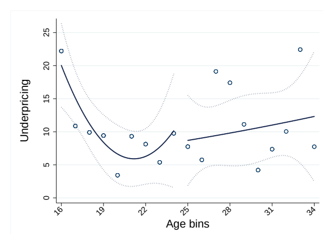
Fig. 11. Underpricing by age with arbitrary thresholds. This figure plots the average outcome by forcing variable for arbitrary thresholds. In Panel (A), the arbitrary threshold is the median value of the forcing variable, conditional on the forcing variable being higher than the cutoff. In Panel (B), the arbitrary threshold is the 25th percentile of the forcing variable, conditional on the forcing variable being higher than the cutoff. In Panel (C), the arbitrary threshold is the 75th percentile of the forcing variable, conditional on the forcing variable being higher than the cutoff. Fitted values come from a quadratic fit on both sides of the arbitrary cutoff. 95% confidence intervals are reported with dotted lines.



(A)



(B)



(C)

Appendix A. Downloading and parsing N-SAR filings

The 77o item of the N-SAR filing asks the filer whether it was involved in affiliated transactions pursuant to the 10(f)-3 rule. If the answer is yes, then the filer has to provide additional information about the affiliated transaction in an attachment. We download from the SEC EDGAR database the 104,207 N-SAR forms filed in the period January 2001 to December 2014. This time span covers the affiliated transactions executed in the period 2001-2013, because an N-SAR form filed in year X can contain information about year X-1. Since 2001, institutions are instructed to name their attachment type: "EX-99.77O 10f-3 RULE." However, a non-negligible number of attachments is filed with a wrong or incomplete name. Hence, we do not rely only on that tag to find the attachments we are interested in. We focus on the N-SAR filings that satisfy at least one of the following (case insensitive) criteria:

- contain in the main form or in any attachment the string "077 O000000 Y";
- contain in the main form or in any attachment the string "10f";
- contain in the main form or in any attachment the string "77o."

Using these criteria, we keep many false positives that do not contain a 10(f)-3 attachment. Our objective is to minimize false negatives, so as to lose the smallest possible amount of information.[26] These criteria leave us with 10,622 N-SAR filings. We parse them manually because the reporting format differs considerably, both between and within investment companies. Figure A1 provides an example of a 10(f)-3 attachment to the N-SAR filings.

[Figure A1 about here.]

[26]Under these criteria, false negatives are N-SAR filings that contain a 10f-3 attachment, but: i) mistakenly answer "NO" to the 77o item, and ii) do not contain the terms "10f" or "77o" in the entire N-SAR document and its attachments.

10(f)-3 attachments report information about both equity and bond issues. We hand-collect information about equity issues only. Sometimes the filings explicitly distinguish the two categories; most of the time, however, we have to infer the kind of security issued. For bond issues, filings often report the maturity date or the yield to maturity; the name of the fund receiving an allocation often reveals whether it is a bond/municipal fund or an equity fund; the reported offer price is typically close to 100 for bond issues; etc. When no such information is provided and we are unable to distinguish equity from bond issues, we store the observation in our dataset in order to minimize false negatives.[27] In this way, we collect 18,872 observations at the issue-"investor"-broker level, meaning that we observe the number of shares allocated to investor f in IPO i by broker b. The "investor" can be a fund, a sub-portfolio of a fund, or an investment management company.

We match 10(f)-3 issuers to SDC issuers mainly by using issuer names and issue dates. We complement the matching with other pieces of information (such as the offer price and the number of shares issued) to increase the accuracy of the match. Moreover, we match 10(f)-3 underwriters to SDC underwriters by name, taking into account name changes and M&A activities. The matching with SDC allows us to disentangle IPOs and SEOs and to focus on IPOs that satisfy the usual filters applied in the literature. This leaves us with 8,828 IPO-investor-broker observations.

We identify and exclude duplicates. Duplicates arise when distinct N-SAR forms report the same information about fund f receiving n shares in the IPO i from broker b. This happens, for example, when an investment company reports the same information both in the annual and semi-annual N-SAR filings (both NSAR-B and NSAR-A).

Some 10(f)-3 attachments contain missing values. For example the amount of shares

[27]False positives are lost when we match our 10(f)-3 data with the SDC database. Hence, they do not constitute a problem.

allocated to affiliated funds is missing for about 5% of the observations, before any cleaning. We use information from other filings to fill in some of these missing values. For example, if the individual number of shares n of IPO i allocated to the fund f affiliated to underwriter j is missing in a filing, but we observe the total number of shares W allocated to the adviser of fund f, then, if other filings report the individual number of shares m received by other funds with the same adviser, we can find out n as: $n = W - m$. In this way, we reduce the percentage of observations with missing allocations to about 1.5%. This implies that we slightly underestimate the total percentage of shares allocated to affiliated funds at the IPO level ($AffiliatedAllocPerc$). The allocation dummy ($AffiliatedAllocDummy$), however, is not affected by this problem.

Fig. A1. An example of a 10(f)-3 attachment to the N-SAR form

FORM 10f-3
Registered Domestic Securities and Government Securities

FUND: The UBS Funds - UBS U.S. Small Cap Growth Fund
Name of Adviser or Sub-Adviser: UBS Global Asset Management (Americas) Inc.
1. Issuer: Green Dot Corp. - Class A
2. Date of Purchase: 7/21/2010 3. Date offering commenced: 7/21/2010
4. Underwriter(s) from whom purchased: JP Morgan Chase Fleming
5. "Affiliated Underwriter" managing or participating in syndicate:
UBS Investment Bank
6. Aggregate principal amount or number of shares purchased: 20,000 shares (firmwide)
7. Aggregate principal amount or total number of shares of offering: 4,560,000 shares
8. Purchase price per unit or share(net of fees and expenses): $36.00
9. Initial public offering price per unit or share: $36.00
10. Commission, spread or profit: ____________% $_1.512_________
11. Have the following conditions been satisfied?

FUND: THE UBS Funds - UBS High Yield Fund
Name of Adviser or Sub-Adviser: UBS Global Asset Management (Americas) Inc.
1. Issuer: Pride International Inc. 6 7/8% due 8/15/2020
2. Date of Purchase: 8/03/2010 3. Date offering commenced: 8/03/2010
4. Underwriter(s) from whom purchased: Goldman Sachs & Co.
5. "Affiliated Underwriter" managing or participating in syndicate:
UBS Investment Bank
6. Aggregate principal amount or number of shares purchased: $500, 000 firmwide
7. Aggregate principal amount or total number of shares of offering: $900,000,000
8. Purchase price (net of fees and expenses): $100.00
9. Initial public offering price: $100.00
10. Commission, spread or profit: .735% $____________
11. Have the following conditions been satisfied?

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