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Nepotism in IPOs: Consequences for Issuers and Investors

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Abstract

IPO underwriters have an incentive to underprice an IPO when they allocate shares to their affiliated funds. We label this conflict of interest "supernepotism" and we analyze its effect on IPO pricing. Using a regression discontinuity design (RDD) on a novel hand-collected data set, we find that higher allocations to underwriter-affiliated funds cause higher IPO underpricing. Our evidence suggests that supernepotism has monetary costs for issuers.

I. Introduction

When taking a company public, an investment bank that is part of a banking group with an asset management arm has an incentive to underprice the IPO if it expects funds affiliated with its bank to receive IPO shares. We empirically examine this conflict of interest and document its consequences for IPO pricing. Our evidence supports the view that this incentive induces banks to underprice IPOs by economically significant amounts.

In the traditional IPO process, the underwriting bank has the primary say over the offering price, as well as largely controlling the initial share allocation. When an IPO underwriter is affiliated with a fund manager, three potential conflicts of interest arise. First, the underwriter may allocate shares in overpriced ("cold") IPOs

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

While fundamentally different, the nepotism and supernepotism hypotheses are not mutually exclusive. Under nepotism, the underwriting bank allocates more IPO shares to its affiliated funds once it realizes that the IPO is underpriced. The IPO issuer does not incur any incremental cost, relative to the allocation of those same underpriced shares to a different investor. Under supernepotism, however, the bank underprices the IPO with the intention of allocating shares to its affiliated funds, and it underprices the IPO more than if allocating shares to its affiliates was not possible. To benefit its asset management arm, the bank intentionally imposes a monetary cost on the IPO issuer.

Using a hand-collected data set of U.S. IPO allocations, we find support for the supernepotism hypothesis in a regression discontinuity design (RDD) setting: a 1 percentage point increase in IPO allocations to affiliated funds leads to an estimated increase in underpricing of 5.4 percentage points, translating to an additional $11 million left on the table by the issuer. Discussing the plausibility of this estimate, we argue that the loss in underwriting fees because of the additional underpricing is more than offset by other benefits to the bank. 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 documented in the existing literature (Ritter and Zhang (2007)).

To construct our data set, we rely on rule 10f-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.[1] Our final data set includes 1,294 IPOs underwritten by 64 banks with affiliates.

Identifying the causal effect of affiliated IPO allocations on underpricing is challenging because allocations and prices are jointly determined. As the outcome of profit-maximizing decisions by investment banks, both are most likely affected by firm characteristics and other unobserved factors. We argue that rule 10f-3 provides the institutional setting we need to single out the effect we want to identify. This rule sets a threshold, requiring issuers to be at least 3 years old before the underwriter can allocate shares to its affiliated funds. Therefore, the size and the probability of underwriter-affiliated allocations will jump discontinuously when the age of the issuing firm reaches the cutoff date. We use a fuzzy RDD setting to exploit this discontinuity and estimate the effect of the treatment (affiliated allocations) on the outcome (underpricing) while eliminating any observed or unobserved

[1]As detailed in Appendix A, we manually gather data from reports spanning 2001–2014, which constrains our sample to the period from 2001 to 2013.

confounding factors. Intuitively, firms that go public at slightly >3 years of age are similar, on average, to firms that go public when slightly younger. Their IPOs should have similar levels of underpricing. If those levels differ, rule 10f-3 lets us estimate the causal effect of affiliated allocations on underpricing.

A large body of literature investigates the role played by conflicts of interest within the IPO book-building process, providing extensive evidence that underwriters allocate IPO shares in ways that could be detrimental to their issuers.[2] Several researchers examine the hypothesis that underwriters preferentially allocate IPO shares to favored investors, who give back part of the underpricing gains in the form of brokerage commissions (the "favored-investor conflict" hypothesis). Using an event-study methodology, Goldstein, Irvine, and Puckett (2011) find that underwriters' brokerage commission revenues are abnormally high in the period preceding hot IPOs. Consistent with Nimalendran, Ritter, and Zhang (2007), they find that one strategy used to increase commissions is to churn shares through round-trip trades in liquid stocks. Moreover, Reuter (2006) and Jenkinson, Jones, and Suntheim (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.

Other conflicts of interest with documented effects on IPO allocations include "laddering," which involves a quid pro quo arrangement between underwriters and their clients: Investors receive IPO allocations in exchange for a promise to buy additional shares in the aftermarket (Griffin, Harris, and Topaloglu (2007)). Liu and Ritter (2010) focus on "spinning," the practice of allocating hot shares to corporate executives to influence their decision to hire the investment bank for future services; they find that these executives are less likely to switch investment bankers in follow-on offers. In the U.S. market, 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), however, finds large cross-country differences in the types of conflicts of interest that affect the allocation of IPO shares to affiliated funds.

While we are not the first to propose a causal relationship between discretional allocations and underpricing, our article makes several distinct contributions. First, we extend this causal hypothesis to the context of allocations to affiliated funds (our "supernepotism hypothesis"). Second, we analyze the interaction between the supernepotism conflict and the favored-investors conflict. For supernepotism to affect underpricing, it must be the case that there is an incremental benefit associated with allocating underpriced shares to affiliated investors, relative to favored, but unaffiliated, investors. We argue that the allocations to affiliated investors also result in increased kickback revenues from the favored investors; we sketch a model to illustrate our logic. Our analysis suggests that the supernepotism conflict and the favored-investors conflict reinforce each other. Third, we single out the causal effects of affiliated allocations on IPO underpricing, using a careful identification strategy. Fourth, we hand-collect our data set from actual IPO allocations rather than relying on end-of-quarter holdings. Among other benefits, our data and findings enable us to reinterpret the results of earlier research. For example, consistent with

[2]See Ljungqvist (2007) for a survey of the early literature.

the existence of costly agency problems, Berzins, Liu, and Trzcinka (2013) find that bank-affiliated funds significantly underperform independent funds. Using quarterly holdings data, 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. Our study indicates that these results are unlikely to be driven by allocations in the IPO primary market. Other factors, which go beyond the scope of this article, appear to be driving the results of those previous studies (e.g., affiliated funds' trading choices in the IPO aftermarket).

II. Intuition and Motivation

Conflicts of interest faced by IPO underwriters have long been documented. For example, it is well-known that underwriters often underprice IPOs and allocate shares to favored investors in return for kickbacks in the form of trading commissions. We postulate another reason for an underwriter to act in a self-serving manner: If the underwriter is part of a banking group with an asset management arm, it has an incentive to underprice the IPO to benefit its affiliated funds. We call this conflict "supernepotism."

In this section, we sketch a simple model to clarify the tradeoffs faced by the underwriter. One might expect supernepotism to mitigate, or be tempered by the favored-investors conflict. Instead, these two conflicts of interest appear to reinforce each other. The key intuition emerging from our analysis is that allocating shares to affiliated funds, and the extra underpricing associated with it also benefits favored funds, and thus indirectly boosts the underwriter's kickbacks.[3]

Consider an underwriter who is conducting the IPO of an unlevered firm. There are two possible equally likely states: good and bad. The IPO firm is worth \$1 in the good state and 0 in the bad state. The existing shareholders of the firm are selling 100% of their stakes and no new funds are raised, so the fair price of this IPO when its state is not known is \$0.5. Everyone is risk neutral and there is no discounting. The underwriter decides which investors to include in the IPO, the price at which the IPO shares are sold (i.e., P, with $P \in (0,1)$), and the final allocation of shares to the investors. Using the proceeds from the sale, the firm's existing shareholders pay the underwriter a commission, cP, at the completion of the IPO, where c is the commission spread.

Our model includes three types of investors:

- **Favored investors** receive allocations only when the IPO is underpriced. These clients pay kickbacks to the underwriter. If they pay the underwriter a fraction, k, of their expected revenues from investing in the IPO, and if the IPO is underpriced, then the underwriter allocates IPO shares to them. If these clients do not pay kickbacks, then they do not receive allocations.[4]

[3]Details and proofs of our model can be found in the Supplementary Material.

[4]This way of modeling the kickback game is consistent with Goldstein et al. (2011), who show that institutional investors pay most of their kickbacks during the 10 days preceding the IPO, and thus only know the expected underpricing.

- **Affiliated funds** are managed by the underwriter and can receive IPO allocations. We model the incentives of the underwriter by assuming that its profit function is proportional to these funds' underpricing gains at the rate m. The parameter m is the percentage management fee earned by the fund managers; it captures, in reduced form, the present value of any additional gains from larger fund inflows because of the underpricing.
- **Regular investors** include other independent institutions and retail investors. They can decide whether to participate in the IPO or not. Regular investors consider the fact that the underwriter may give preferential treatment to favored clients and affiliated funds. We assume that the underwriter needs regular investors to participate, or the IPO fails.

The timeline of our model is as follows:

- Time 0 ("Roadshow" stage): The underwriter announces the IPO price (P) and chooses the investors to whom to offer the IPO. Everyone observes P and to whom the IPO is offered.
- Time 1 ("Participation decision" stage): Regular investors decide whether to participate or not. Favored investors pay kickbacks if they were offered the IPO.
- Time 2 ("Final allocations" stage): The underwriter observes the true state of the firm and makes the final allocation of shares within the subset of investors to whom the IPO was offered. The IPO is completed.
- Time 3 ("Payoffs realization" stage): The IPO firm's final payoffs are realized, and all outstanding claims are settled.

Our analysis shows that the equilibrium outcomes of this model are as follows. If there are only regular investors, the underwriter does not underprice the IPO. To maximize underwriting commissions, the underwriter chooses the highest possible IPO price, which is the fair price \$0.5.[5] When the underwriter can also allocate shares to favored investors, but not to affiliated funds, the equilibrium outcome is intuitive: When $k<c$, the underwriter has no incentive to allocate any shares to favored investors; it allocates all the shares to regular investors and does not underprice the IPO. When $k>c$, the underwriter allocates some shares to favored investors; the regular investors face a winner's curse situation, and the underwriter must underprice the IPO to ensure their participation. Depending on how high k is, the underwriter is limited either by the participation constraint of the regular investors or by that of the IPO firm.

So far, it might appear that the underwriter allocates shares to whichever investor category maximizes its direct linear payoff, subject to the participation constraints of the regular investors and of the IPO firm. This conclusion is not correct in the situation of interest to us, however. When it can allocate shares to all three types of investors—regular investors, favored investors, and affiliated funds—the underwriter may allocate shares to affiliated funds even when $m<c$ and $m<k$. This seemingly paradoxical outcome arises from complementarity effects between allocations to favored investors and those to affiliated funds. Such complementarities are especially prominent when $k>c$ and when the IPO firm

[5]In our model, regular investors play a role similar to that of uninformed investors in Rock (1986).

has a low reservation price (a realistic assumption for IPO firms that are only a little >3 years old) making it possible for the underwriter to choose a high level of underpricing. First, for moderately high values of k, higher allocations to affiliated funds imply a higher level of underpricing in equilibrium, to compensate regular investors for the winner's curse. This higher level of underpricing increases the profits of favored investors, and so also increases the underwriter's kickbacks. Therefore, increasing allocations to affiliated funds may increase the kickbacks from favored investors. Second, for very high values of k, the underwriter has an incentive to underprice as much as possible and to allocate as many shares as possible to both favored investors and affiliated funds, subject to the participation constraint of the IPO firm (regular investors make a profit in expectation).

Overall, the key insight from this simple model is that, given reasonable assumptions, allocations to affiliated funds and favored investors work together to further the underwriter's interests. The very possibility that the underwriter may allocate shares to its affiliated funds increases the winner's curse situation of regular investors. Keeping regular investors on board requires further underpricing, which boosts the returns of the underwriter's affiliated funds and the kickbacks from its favored investors.

III. Data and Summary Statistics

Section 10(f) of the Investment Company Act of 1940 prohibits underwriters from selling shares of a security to funds that are affiliated with a member of the underwriter's syndicate. This regulation was amended in 1958 and in subsequent years to exempt certain transactions. During this study's sample period, rule 10f-3 of the Act permitted funds to buy securities underwritten by their parent banks if certain conditions were satisfied. Four of these conditions are of particular importance here: i) the issuer must have been in continuous operation for at least 3 years before the offering, including the operations of any of its predecessors; ii) the securities are offered under a firm-commitment contract;[6] iii) the affiliated transaction is executed by a syndicate member other than the affiliated underwriter;[7] iv) any transaction pursuant to rule 10f-3 is reported on the investment company's SEC form N-SAR, attaching a written record of the details of each transaction.

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

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

[6]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.

[7]For example, consider Issuer X, underwritten by Banks A and B. Rule 10f-3 says that funds affiliated with Bank A can receive allocations only from Bank B and, vice versa, funds affiliated with Bank B can receive allocations only from Bank A.

A. IPO Data

We use the SDC database to identify IPOs made in the United States from 2001 to 2013.[8] We exclude all American Depositary 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 an offer price <\$5. Moreover, we require IPOs to have a match with the CRSP database 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 primary or secondary shares, the total assets of the issuer before the IPO,[9] 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 (see footnote 7). When the founding year is not available on the Ritter website, we use the founding date available on SDC. Underwriters' reputations are ranked on the Ritter website using numbers ranging from 1 (lowest) to 9 (highest). These rankings are described in Loughran and Ritter (2004) and are an adjustment of the Carter and Manaster (1990) rankings. Appendix Table B1 describes the IPO variables we compute by matching the SDC, CRSP, and Ritter data.

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

The first three conditions are a direct consequence of the rule 10f-3 requirements. The rationale behind our fourth condition is that underwriters who have never been involved in a 10f-3 transaction might not have any affiliated funds.[10] From our original sample of 1,294 IPOs, we count 1,086 IPOs that are eligible for affiliated transactions; 208 IPOs do not satisfy at least one of the four requirements. Figure 1 plots the number of IPOs by year, distinguishing between eligible and non-eligible IPOs. The percentage of eligible IPOs, at about 84% on average, appears to be stable in the period 2001–2013.

Table 1, Panel A provides summary statistics for the 1,086 eligible IPOs (columns 2–4), the 208 non-eligible IPOs (columns 5–7), and the sample of

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

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

[10]This condition may not perfectly identify IPOs whose underwriters have affiliated funds. We cross-checked our data with the list of affiliated underwriters in Pratobevera (2024), confirming that our classification is highly reliable.

FIGURE 1

Number of IPOs by Year

Figure 1 shows the number of eligible and non-eligible IPOs by year.

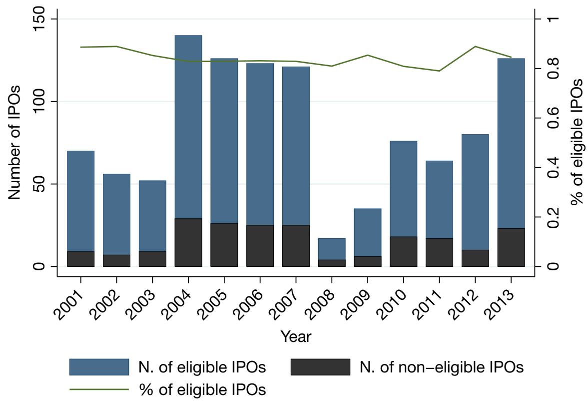

TABLE 1

Summary Statistics of IPO and Allocation Data

Table 1 provides summary statistics at the issuer level for 1,086 eligible IPOs (columns 2–4), 208 non-eligible IPOs (columns 5–7), and 217 IPOs used in our main RDD analyses (columns 8–10). We define an IPO as "eligible" if it satisfies these conditions: The issuer is at least 3 years old, the securities are issued under a firm-commitment contract, there is more than one underwriter in the syndicate, and at least one lead underwriter has been involved in a 10f-3 transaction in our sample. The RDD sample comprises 152 eligible IPOs with $3 \leq Age < 6$ years and 65 IPOs that satisfy all the other eligibility requirements but are <3 years old. Panel A summarizes the IPO characteristics, and Panel B summarizes the allocation data. For each variable, the table reports its average (mean), its median (p50), and its standard deviation (sd). IPO and allocation variables are defined in Appendix Table B1.

	Eligible			Non-Eligible			RDD Sample		
	Mean	p50	sd	mean	p50	sd	mean	p50	sd
Panel A. IPO Characteristics									
Underpricing (%)	14.2	9.09	19.4	5.13	1.16	13.9	12.1	5.00	19.4
Age (years)	22.9	11	27.7	11.1	5	22.5	3.3	4	1.6
Proceeds ($ million)	219	117	266	86.7	48.2	112	196	108	227
Assets ($ billion)	1,351	218	2,373	1,123	51.3	2,455	1,354	190	2,446
Adjustment (%)	−1.59	0	13.3	−4.49	0	11.2	−1.84	0	12.6
GrossSpread (%)	6.63	7	0.73	6.93	7	0.66	6.63	7	0.70
NumberLeadManagers	2.38	2	1.47	1.69	1	1.13	2.49	2	1.67
NumberSyndicateMembers	7.51	6	4.59	4.80	4	3.34	7.54	6	4.20
LengthIPOprocess (months)	4.41	3.37	3.57	4.39	3.60	3.39	3.88	3.19	3.14
OnlyPrimaryShares	0.52	1	0.50	0.79	1	0.41	0.69	1	0.46
Nasdaq	0.61	1	0.49	0.75	1	0.43	0.69	1	0.46
Foreign	0.097	0	0.30	0.21	0	0.41	0.20	0	0.40
VentureCapitalBack	0.45	0	0.50	0.31	0	0.46	0.47	0	0.50
HighRankDummy	0.78	1	0.41	0.25	0	0.44	0.78	1	0.42
Panel B. Allocation Data									
AffiliatedAllocPerc (%)	1.44	0.12	2.36	0.077	0	0.68	1.02	0	2.06
AffiliatedAllocDummy	0.56	1	0.5	0.082	0	0.27	0.42	0	0.5
IndependentAllocPerc (%)	18.3	16.1	13.3	10.1	5.73	12.0	15.8	13.2	13.4

217 IPOs used in our main RDD analyses (columns 8–10). The RDD sample comprises 152 eligible IPOs with $3 \leq Age < 6$ years and 65 IPOs that satisfy all the other eligibility requirements but are <3 years old. All non-dummy variables except *Age* are winsorized at the 2.5% level.[11] Table 1 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. Except for the firms' ages, overall the RDD sample is similar to the total sample of eligible and non-eligible IPOs.

B. Allocation Data

At the time of our study, investment companies reported their affiliated transactions to the SEC through their filing of N-SAR forms. We downloaded from the SEC EDGAR database all the N-SAR forms filed from Jan. 2001 to Dec. 2014 and collected 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 data set, which contains: IPO identifiers (issuer name, CUSIP, and issue date); the name of the affiliated fund and/or the subportfolio of the fund and/or the investment company that receives an allocation; the number of shares received by the affiliated fund and/or by the subportfolio of the fund and/or by the 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. Thus, we can observe the number of shares allocated at the IPO-investor-broker level.

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: $AffiliatedAllocPerc_i = \frac{A_i}{N_i} \times 100$.

AffiliatedAllocDummy is a dummy variable equal to 1 if at least one share is allocated to an affiliated fund: $AffiliatedAllocDummy_i = 1(A_i > 0)$.

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 (i.e., 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. We let 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

[11]We do not winsorize *Age* because it is the forcing variable in the RDD setting; see Section IV.

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proxy for the percentage of the issue allocated to independent funds as:[12] $IndependentAllocPerc_i = \frac{H_i - A_i}{N_i} \times 100$.

To reduce the impact of potential data errors and outliers, we winsorize the allocation variables *AffiliatedAllocPerc* and *IndependentAllocPerc* at the 2.5% level. Table 1, Panel B, summarizes the allocation data at the issuer level for the 1,086 eligible IPOs (columns 2–4), the 208 non-eligible IPOs (columns 5–7), and the subsample of 217 IPOs used in our main RDD analyses (columns 8–10). Of the eligible IPOs, 611, or about 56%, involve at least one affiliated transaction and, on average, 1.44% of the issue is allocated to funds affiliated with the underwriters. Conditional on involving at least one 10f-3 transaction, then, 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%.

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 <3 years old. There are several reasons why underwriters might have allocated shares to their affiliated funds in these cases. First, we may have misclassified these IPOs as "non-eligible": Errors in the issuers' founding dates or the existence of unknown predecessors could have led us to miscalculate their age. Second, 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 takes into account the general principles behind the 10f-3 rule when interpreting and applying it. Consequently, certain transactions that seem to formally violate the rule could, in fact, be allowed.[13] Third, the underwriters might have broken the 10f-3 rule, allocating shares of non-eligible issuers to their affiliated funds. When a search on Google provides information consistent with the founding dates contained in our data set, we flag the IPO as non-eligible because of the firm's age.

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

[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 data set and in the s12 database.

[13]One popular example dates 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 <3 years old. These securities were co-issued with and 100% guaranteed by another company that was >3 years old and, thus, was compliant with the 10f-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. 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.

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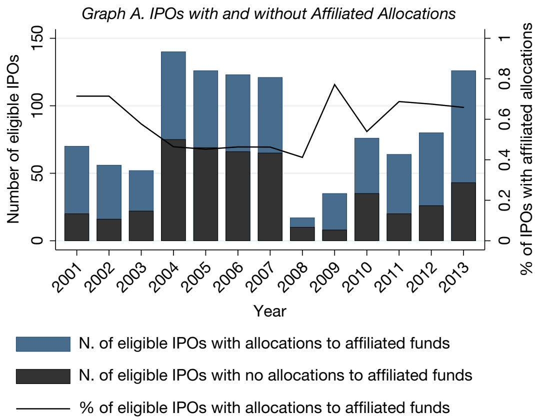
FIGURE 2

Institutional IPO Allocations by Year

Figure 2 shows the affiliated and independent allocations from 2001 to 2013 of 1,086 eligible IPOs. Graph 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. Graph 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.



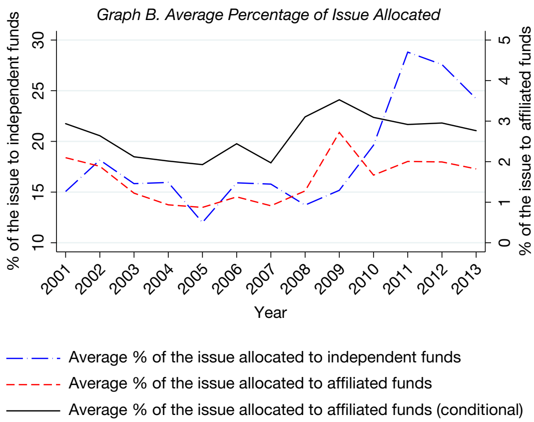


Figure 2 shows the average allocations to affiliated and independent funds over the period 2001–2013 for the 1,086 eligible IPOs. Graph A shows that the percentage of IPOs with affiliated allocations ranges from a minimum of 41% in 2008 to a peak of 77% in 2009, with no apparent trend in the period 2001–2013. 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. These results mean that in periods when underwriters are more likely to allocate 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 2002, when the SEC amended rule 10f-3, loosening some of its constraints. In particular, after 2002 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 rule 10f-3.

To assess the contribution of our novel data set, it is worth comparing these summary statistics with those of Ritter and Zhang (2007), as they use 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 ~26% of the IPOs in 2001, while we find 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. To further investigate the merits of our novel data set, we identify affiliated funds in the Spectrum 1&2 database and build a proxy of their IPO allocations based on end-of-quarter holdings, as in the prior literature. We find that the correlation between actual allocations and the end-of-quarter holdings of affiliated funds in eligible IPOs is only 0.52. The average end-of-quarter holding of affiliated funds is 0.59%, which is much lower than their average IPO allocation (1.44%). Affiliated funds have a positive end-of-quarter holding in 30% of the IPOs while receiving a positive allocation in 56% of them. More importantly, the unconditional correlation between underpricing and the percentage of affiliated allocations is 0.12, while the correlation between underpricing and the percentage of affiliated end-of-quarter holdings is only 0.03. Average underpricing is 19.4% in IPOs with affiliated allocations and 7.6% in IPOs with no affiliated allocations; average underpricing is 18.3% in IPOs with affiliated end-of-quarter holdings and 12.5% in IPOs with no affiliated end-of-quarter holdings.

IV. The Effect of Affiliated Allocations on Underpricing

Rule 10f-3 provides the institutional setting we need to design a quasi-experiment to test our supernepotism hypothesis and identify a causal link between affiliated allocations and underpricing. For the underwriter to be permitted to allocate shares to its affiliated funds, rule 10f-3 requires issuers to be at least 3 years old. Therefore, the probability of allocating some shares to affiliated funds should discontinuously increase at the 3-year cutoff point. This source of exogenous variation allows us to implement a fuzzy regression discontinuity design (RDD).[14]

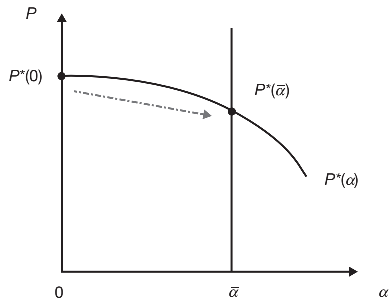
In RDD terminology, *Underpricing* is the "outcome" variable; our affiliated allocation measures—*AffiliatedAllocPerc* and *AffiliatedAllocDummy*—are the "treatment" variables; and *Age* is the "forcing" variable that determines the assignment-to-treatment status through the 3-year cutoff. We are interested in the

[14]As observed in Section III, the 3-year cutoff does not perfectly determine the affiliated allocation decision, either below or above the threshold. Therefore, a sharp RDD does not fit our setting.

FIGURE 3

Identification Strategy

Figure 3 visualizes an intuitive representation of our identification strategy, where P is the IPO price and α is the percentage allocation to affiliated funds.



causal effect of the treatment on the outcome. A fuzzy RDD exploits the discontinuous variation in the treatment status provided by the forcing variable to identify that causal effect.

The RDD framework helps us overcome the joint endogeneity of affiliated allocations and underpricing by letting us approximate an ideal experimental setup, in which the possibility of allocating shares to underwriter-affiliated funds is randomly assigned. Consider an underwriter who is hired by several firms of random ages to perform their IPOs. Firms that choose to go public at 2 years old probably differ in many ways from those that go public in their twenties. These IPO-specific differences may influence both the allocation and the pricing decisions of the underwriter, making it difficult for us to identify causal effects. If we consider an arbitrarily small neighborhood around the 3-year cutoff point, however, we can compare firms that differ discontinuously in their treatment probability (i.e., firms just over and under 3 years old), but do not differ greatly in other ways.

We assume that only the treatment (the affiliated allocations) will change discontinuously at the cutoff point, while the conditional expectation function of all other factors (both observable and unobservable) is continuous. We discuss the validity of this identifying assumption in Section IV.A.

Our identification strategy is illustrated in Figure 3. Consider an underwriter who faces supernepotism incentives and has a profit function such that its optimal choice of the offer price, P, as a function of its affiliated allocations, α, is given by $P^*(\alpha)$.[15] If the underwriter complies with rule 10f-3, its affiliated allocations are constrained to zero when the age of the IPO falls below the cutoff. In this case, the affiliated allocations and optimal price are given by the pair $(0, P^*(0))$. When the age of the IPO is above the cutoff, however, the underwriter can optimally choose P and α to maximize its profits. Letting $\bar{\alpha}$ be the fraction of the issue that can be allocated to affiliated funds, the underwriter chooses the pair $(\bar{\alpha}, P^*(\bar{\alpha}))$. The cutoff thus identifies movements along the $P^*(\alpha)$ function, allowing us to estimate the change in the optimal offer price caused by a change in allocations to affiliated

[15]Within the stylized model of Section II, $P^*(\alpha)$ illustrates the optimal IPO price when the kickback and nepotism conflicts are complements and the binding participation constraint is that of regular investors.

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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 with rule 10f-3.

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

The remaining 143 IPOs that, regardless of their age, do not meet at least one of the other 10f-3 requirements are useful for placebo tests only.

A. Relevance and Exogeneity: Graphical Analysis and Discussion

We follow the RDD literature (Imbens and Lemieux (2008), Lee and Lemieux (2010)) in providing graphical evidence that supports the relevance and exogeneity of the 3-year cutoff.

For it to be a valid instrument in a fuzzy RDD setting, the cutoff must discontinuously affect the treatment variable. Figure 4 plots the average value of

FIGURE 4

Affiliated Allocations by Age

Figure 4 plots average treatments by the forcing variable (age at IPO). We compute the average *AffiliatedAllocDummy* (Graphs A and B) and *AffiliatedAllocPerc* (Graphs C and D) for each age group (bin) of 1-year size. Fitted values come from a linear fit on both sides of the 3-year cutoff in Graphs A and C; they come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$ in Graphs B and D. 95% confidence intervals are reported with dotted lines.

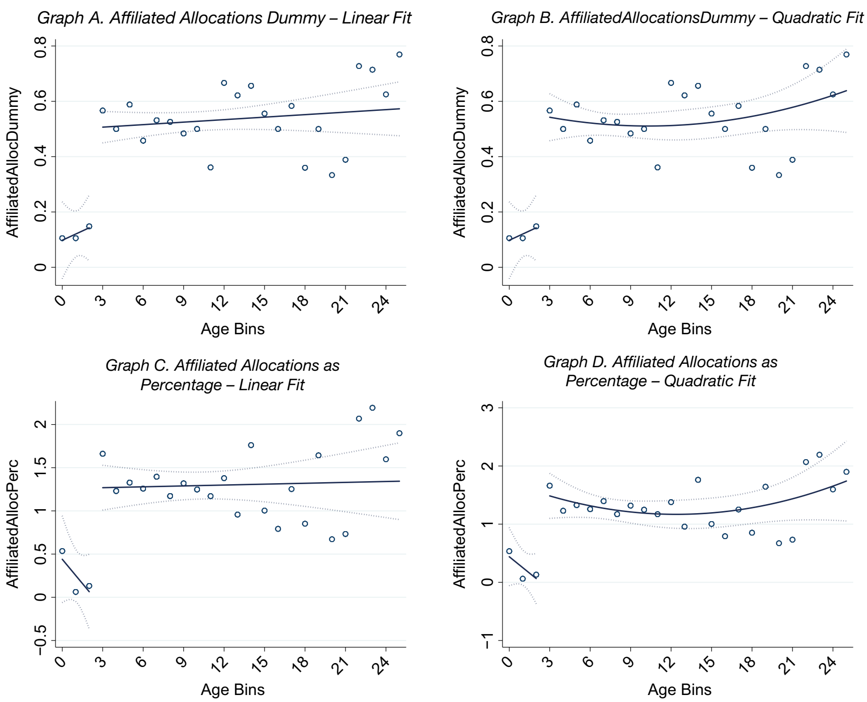
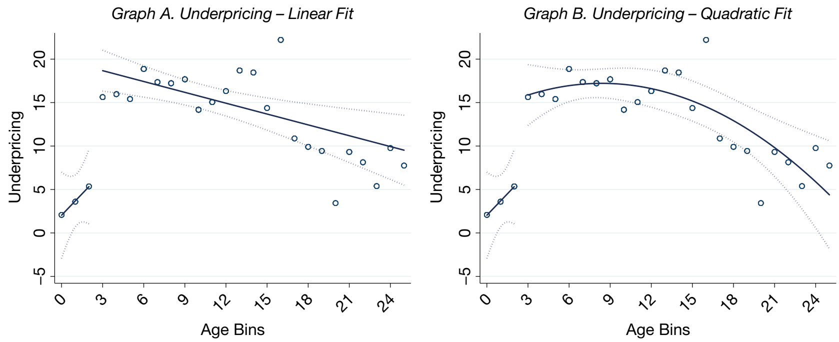


FIGURE 5

Underpricing by Age

Figure 5 plots the average outcome by the forcing variable (age at IPO). We compute average *Underpricing* for each age group (bin) of 1-year size. Fitted values come from a linear fit on both sides of the 3-year cutoff in Graph A; they come from a linear fit for *Age* < 3 and a quadratic fit for 3 ≤ *Age* ≤ 25 in Graph B. 95% confidence intervals are reported with dotted lines.



the variables *AffiliatedAllocDummy* and *AffiliatedAllocPerc* by 1-year age groups (bins). Graphs A and B show that the probability of receiving the treatment jumps at the cutoff. The probability that an IPO involves a 10f-3 transaction is <20% for IPOs below the cutoff but jumps to >50% just above it. A similar pattern holds for the average percentage of the issue allocated to affiliated funds. As shown in Graphs C and D, it is <0.5% below the cutoff but jumps to much >1% above it.

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 jump 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.

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 3-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 10f-3 transactions. Although appealing, this argument is not supported by the evidence. If underwriters were manipulating the length of the IPO process, then we would see a discontinuity, in the form of a jump or a spike, in the variable *LengthIPOprocess* at the cutoff point: 3-year-old firms would experience longer IPO processes because of their underwriters' timing strategy. Figure 6, Graphs B–D, shows this not to be the case. There is no evidence of a discontinuity at the cutoff point for IPOs in general (Graph B), hot IPOs (Graph C), or cold IPOs (Graph D), thus ruling out systematic and selective timing by underwriters. (Hot (cold) IPOs are defined as IPOs with a positive (non-positive) price adjustment during the IPO process.)

Furthermore, if manipulation were a concern, then we might expect a particular group of IPOs to be subject to it: firms that start their going-public process before they are 3 years old, but complete it afterward. We observe that only 17% of

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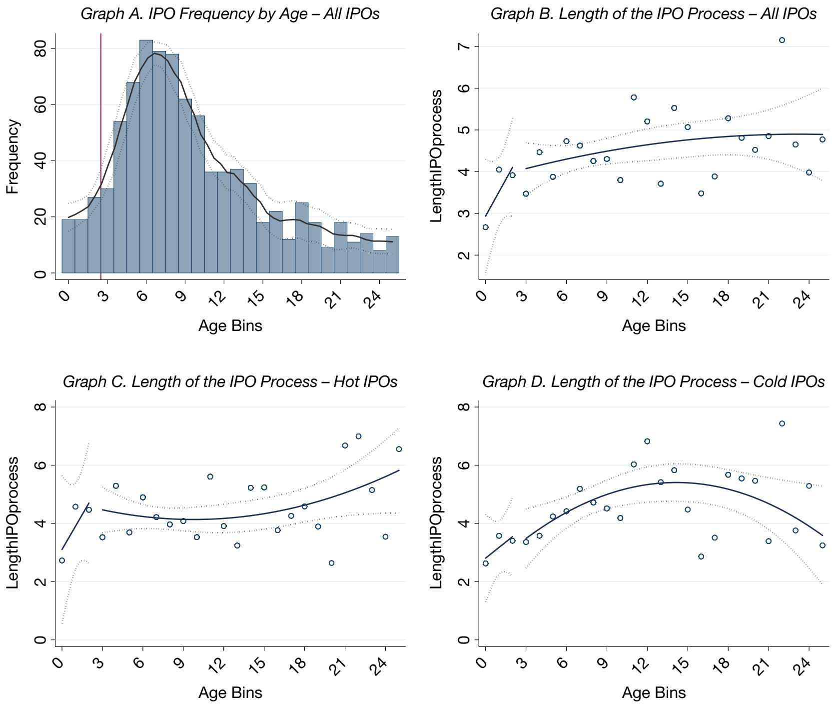
FIGURE 6

Density and IPO Process Length by Age

Figure 6 plots the number of IPOs (Panel A) and the average length of the IPO process (Panels B, C, and D) by the 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 1-year size. In Panels C and D, we split the average *LengthIPOprocess* by hot and cold IPOs, respectively. Hot (cold) IPOs are defined as IPOs with a positive (non-positive) price adjustment during the IPO process (*Adjustment*). 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.



IPOs that start the process when they are 2 years old complete it when they are 3 years old or older. (For comparison, 37% of firms that start the process when they are 3 years old complete it when they are 4 years old or older.) In these 2-year-old IPOs, the average underpricing is 2%, suggesting that their timing, if any, is unrelated to nepotism incentives.

Another possibility is that the underwriter manipulates the age of the issuer by postponing the filing date. Delaying its beginning leaves the length of the IPO process unchanged, preventing us from detecting this manipulation of 3-year-old firms in Figure 6, Panel B, and invalidating our design. We find this argument unconvincing for three reasons. First, underpricing is not the underwriter's sole objective. The desire to accomplish the IPO, and not miss a window of opportunity, pushes the underwriter to not delay the start of the process, as the issuer might otherwise turn to a competing underwriter to complete the IPO. Thus, competition among underwriters 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 its length is a random variable over which the underwriter does not have full control.[16] Third, if underwriters were systematically manipulating firms' ages, then we would observe a jump in the density of the variable *Age* at the cutoff point. Figure 6, Panel A, shows this not to be the case. Overall, the evidence of non-manipulation seems to hold also at the underwriter level. Figure 7 plots by age bin the number of IPOs underwritten by the most important underwriters.[17] Again, there is no general discontinuity in the number of IPOs underwritten by each underwriter at the cutoff point; only one (Wells Fargo) shows a spike.

The identifying assumption of a regression discontinuity design is that the conditional expectation functions of all observable and unobservable factors related to the outcome, other than the treatment variables, 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 discontinuities in the conditional expectation functions of any of these 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 3-year cutoff, but this spike does not seem to be a discontinuity 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.

Similarly, Figure 9 plots the number of IPOs by age in each of the 12 Fama–French industries. The histograms do not show discontinuities in any industry, thus suggesting that industry composition is continuous at the 3-year cutoff.

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

B. Local Linear IV Results

In this subsection, we estimate the effect of underwriter-affiliated allocations on underpricing using a fuzzy RDD.

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 3 years old, $z_i = 1(x_i \geq 0)$. We then estimate several specifications of the following local linear IV model, where $Alloc_i$ is one of our two measures of affiliated allocations,

[16]The random component here 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, and so on.

[17]The 14 most important underwriters are those that are involved in 10f-3 transactions in at least 25 IPOs in our sample. See the Supplementary Material for additional details.

FIGURE 7

Density by Age for Each Underwriter

Figure 7 plots the number of IPOs underwritten by the most important underwriters by age groups (bins) of 1-year size. If an IPO has multiple underwriters, it is included in the subfigures for each of them. All subfigures report histograms and smoothed values from kernel-weighted polynomial regressions with Epanechnikov kernel. 95% confidence intervals are reported with dotted lines.

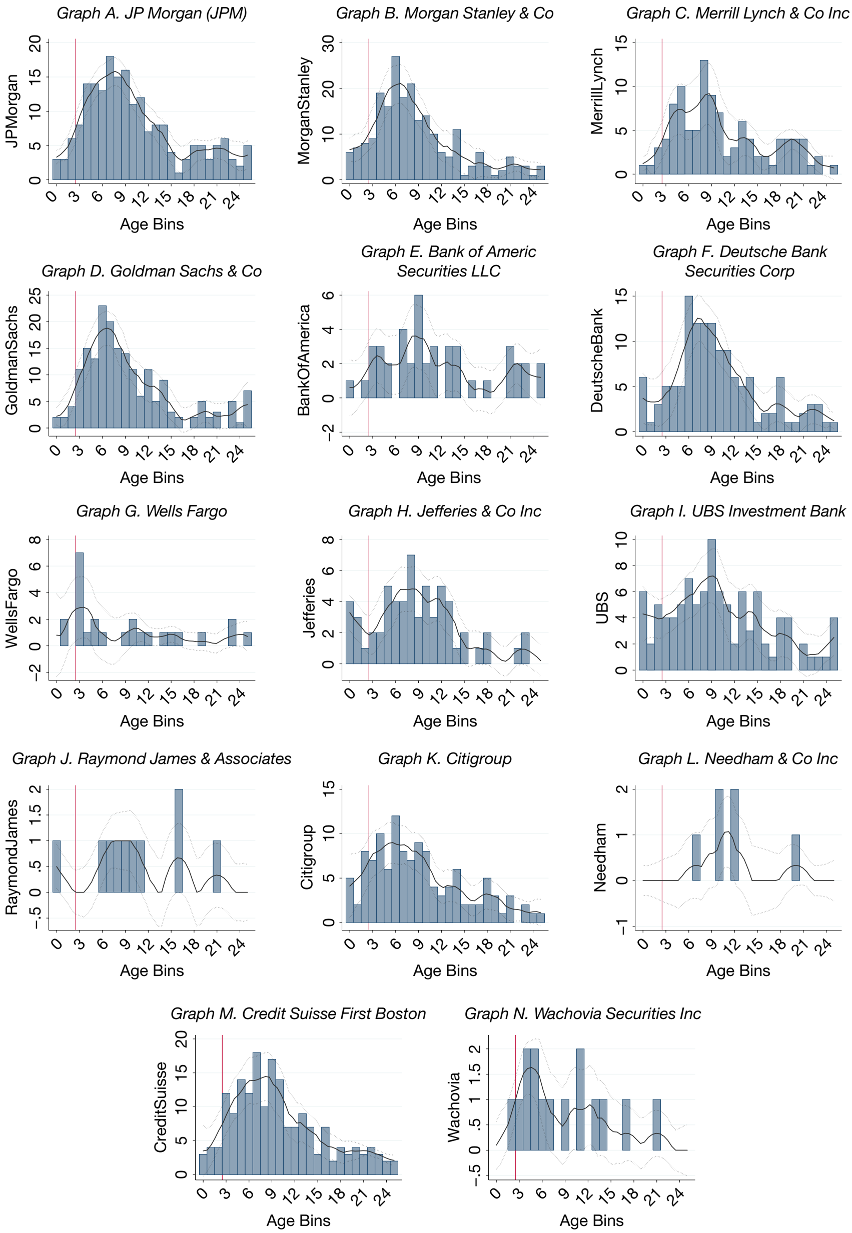
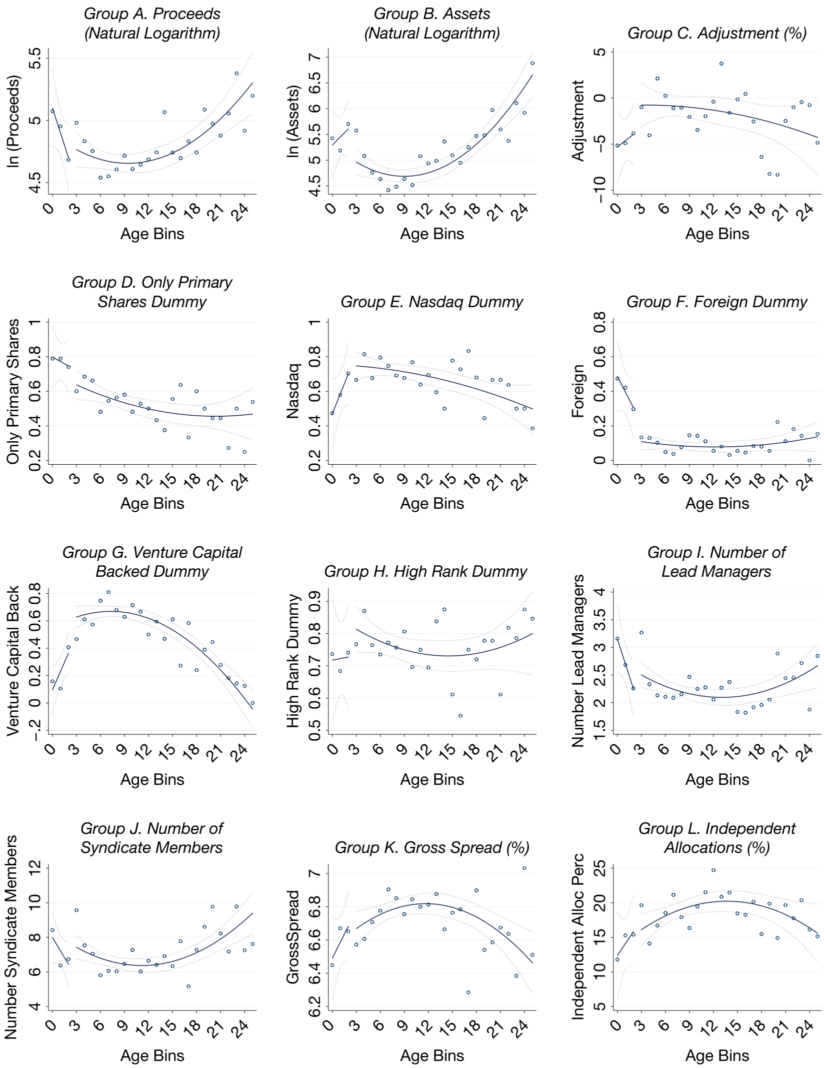


FIGURE 8

Covariates by Age

Figure 8 plots average covariates by the forcing variable (age at IPO). We compute the average value of each control variable by age groups (bins) of 1-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.



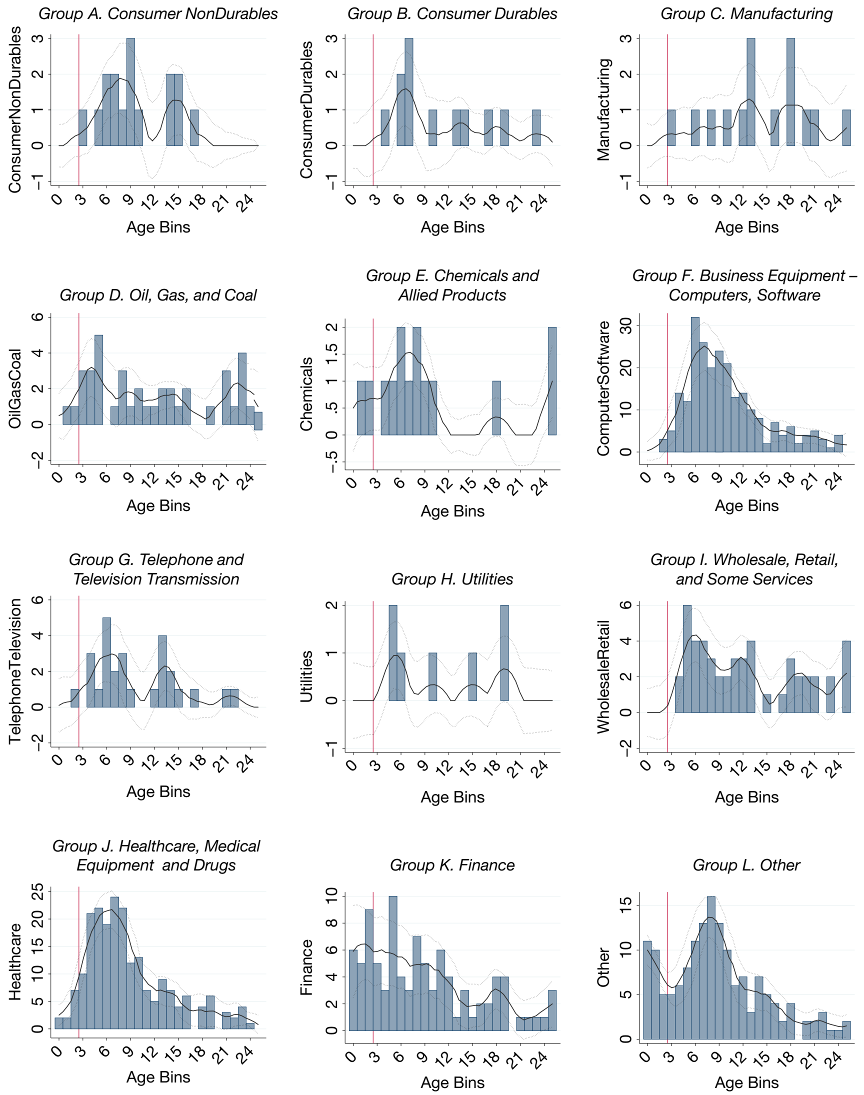
$AffiliatedAllocPerc_i$ or $AffiliatedAllocDummy_i$, and $Underpricing_i$ is the first-day return:

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

FIGURE 9

Density by Age for Each Industry

Figure 9 plots the number of IPOs by age groups (bins) of 1-year size in each of the 12 Fama–French industries. All subfigures report histograms and smoothed values from kernel-weighted polynomial regressions with Epanechnikov kernel. 95% confidence intervals are reported with dotted lines.



As discussed in subsection IV.A, 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 RDD 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 Appendix Table B1), some truly n-year-old firms might fall into the $n+1$ age bin, generating some possible misclassification around the cutoff. Third, the number of values that the forcing variable can take around the threshold is low, with only three distinct values below the cutoff. These three issues affect our choice of bandwidth and standard errors to use.

Concerning bandwidth, h, the trade-off we face goes beyond the usual one related to 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. Given the discrete nature of our forcing variable, however, in this case, we would not be able to control for the underlying relation between *Underpricing* and x. If we choose an ($h>1$e.g.,) $h=3$, then we can control for a local linear relation between the outcome variable and our discrete forcing variable. However, we do so at the cost of using observations that are relatively far from the cutoff point and are therefore less likely to meet the random assignment condition.

Concerning standard errors, clustering by the forcing variable is popular in the literature on RDD (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. Through simulations (unreported here), we confirm that Kolesàr and Rothe's concerns persist in our particular setting, with its low number of clusters and its possible misclassifications around the cutoff. We find that clustered standard errors face a major over-rejection problem in our setting, while robust standard errors seem to be fairly conservative. 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 reasoning, we use robust standard errors and perform our analysis using three symmetric bandwidth levels ($h=1$, $h=2$, and $h=3$) to check the robustness of our results, as reported in Table 2.

Consistent with the supernepotism hypothesis, the coefficients of our affiliated allocation variables are positive in all specifications; they are statistically significant at conventional levels in all specifications but one. Focusing on model 6 of Panel A, which controls for changes in the underlying relation between the outcome and the forcing variables, we find that a 1 percentage point increase in the fraction of the issue allocated to affiliated funds increases underpricing by about 5.4 percentage points. Table 2 also reports the first-stage F statistic, which is always bigger than 10, suggesting that the instrument z is not weak.

For completeness, Table 3 reports the estimates of the reduced-form regression (equation (2)). Results overall are consistent with Figure 5 and Table 2.

$$(2) \qquad Underpricing_i = \theta_0 + \theta_1 z_i + \theta_2 x_i + \theta_3 z_i x_i + \in_i \; with \; x_i \in [-h, h-1]$$

[18]Our simulations show that the power of a 2-sided 5% test can be as low as 15%, depending on parameter values.

TABLE 2

The Effect of Affiliated Allocations on Underpricing—Fuzzy RDD Estimates

Table 2 contains the second-stage coefficients of a local 2SLS regression of *Underpricing* on two measures of affiliated allocations instrumented by z, different values of the bandwidth h. The two measures are *AffiliatedAllocPerc* (Panel A) and *AffiliatedAllocDummy* (Panel B). z is a dummy variable equal to 1 if $Age \geq 3$, and 0 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. Returns and fractions are expressed as percentages. All non-dummy variables except *Age* are winsorized at the 2.5% level. Heteroscedasticity-robust t-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	h = 1	h = 2	h = 2	h = 3	h = 3	h = 3
	1	2	3	4	5	6
Panel A. Affiliated Allocations as Percentage (*AffiliatedAllocPerc*)						
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
Panel B. Affiliated Allocations Dummy (*AffiliatedAllocDummy*)						
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

C. Placebo IPOs

If the 3-year cutoff affects underpricing only through affiliated allocations, then we should observe no discontinuities 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, and so should show no jump in underpricing at the cutoff. Figure 10 plots the average underpricing by age bins for our sample of non-eligible IPOs. As expected, we see no evidence of discontinuities at the 3-year cutoff.

Since the 3-year cutoff set by rule 10f-3 is specific to U.S. regulations, we should observe no jump in underpricing at the cutoff for non-U.S. IPOs. We verify this fact using an SDC sample of 456 European firm-commitment IPOs issued in the

TABLE 3

Reduced-Form Regression

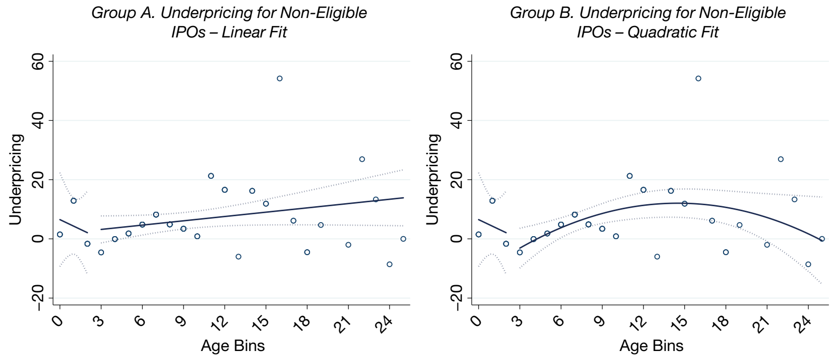
Table 3 contains coefficients of the reduced-form regression of *Underpricing* on *z*, *x*, and *z_x*, for different values of the bandwidth *h*. *z* is a dummy variable equal to 1 if $Age \geq 3$, and 0 otherwise; $x = Age - 3$; and $z\_x = z \cdot x$. Returns and fractions are expressed as percentages. All non-dummy variables except *Age* are winsorized at the 2.5% level. Heteroscedasticity-robust *t*-statistics are in parentheses. Significance levels are denoted as: * 0.1, ** 0.05, *** 0.01.

	h = 1	h = 2	h = 2	h = 3	h = 3	h = 3
	1	2	3	4	5	6
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

FIGURE 10

Underpricing by Age for Non-Eligible IPOs

Figure 10 plots the average outcome by forcing variable (age at IPO) for non-eligible IPOs. We compute average *Underpricing* for each age group (bin) of 1-year size. Fitted values come from a linear fit on both sides of the 3-year cutoff in Graph A; they come from a linear fit for $Age < 3$ and a quadratic fit for $3 \leq Age \leq 25$ in Graph B. 95% confidence intervals are reported with dotted lines.



period 2001–2013.[19] In Figure 11 we plot their average underpricing by age bins and find no evidence of discontinuities at the 3-year threshold.

Following the RDD literature (Imbens and Lemieux (2008)), we check that there are no jumps at non-discontinuity points (i.e., 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 $Age > 3$,

[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.

FIGURE 11

Underpricing by Age for European IPOs

Figure 11 plots the average outcome by forcing variable (age at IPO) for a sample of 456 European firm-commitment IPOs performed in the period 2001–2013. We compute average *Underpricing* for each age group (bin) of 1-year size. Fitted values come from a linear fit on both sides of the 3-year cutoff in Graph A; they come from a linear fit for *Age* < 3 and a quadratic fit for 3 ≤ *Age* ≤ 25 in Graph B. 95% confidence intervals are reported with dotted lines.

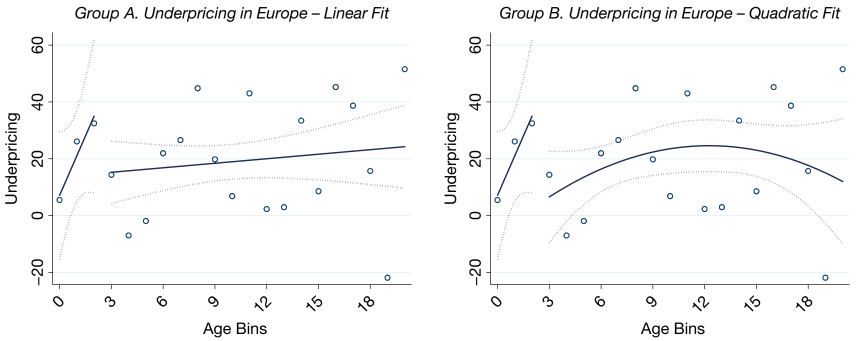
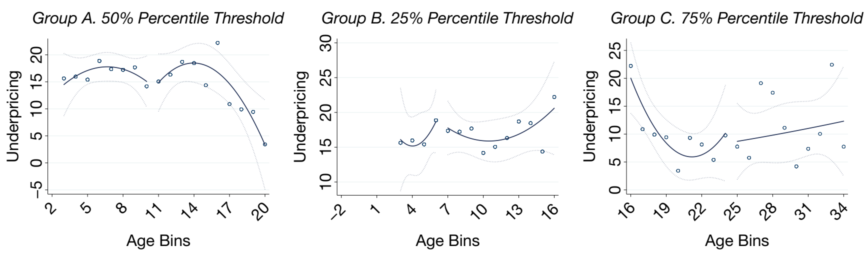


FIGURE 12

Underpricing by Age with Arbitrary Thresholds

Figure 12 plots the average outcome by forcing variable (age at IPO) for arbitrary thresholds. In Graph A, the arbitrary threshold is the median value of the forcing variable, conditional on the forcing variable being higher than the cutoff. In Graph B, the arbitrary threshold is the 25th percentile of the forcing variable, conditional on the forcing variable being higher than the cutoff. In Graph 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.



which is 25 years. Figure 12 plots the average underpricing by age bins around these arbitrary thresholds, and we see no evidence of discontinuities.

D. How Realistic Are Our RDD Estimates?

How plausible is our estimate of the additional underpricing because of affiliated allocations? For underwriters to engage in supernepotism, the loss in underwriting fees must be less than the sum of i) the benefits to the asset management arm, and ii) the impact on kickbacks from favored investors. The loss to the IPO issuer, because of this additional underpricing, can be estimated as follows: From Table 1, the average proceeds in our RDD sample are $196 million, and the average allocation to affiliated funds is 1.02%. The RDD regression estimate in

Table 2 indicates that the additional underpricing resulting from one percentage point of affiliated allocations is 5.43%. Therefore, the additional average underpricing because of affiliated allocations is $1.02 \times 0.0543 = 5.54\%$, and the additional average money left on the table is $0.0554 \times 196 = \$11$ million. From Table 1, the average gross underwriting spread is 6.63%. Therefore, the average loss in underwriting fees because of supernepotism is $0.0663 \times 11 = \$0.73$ million.

The benefits of these affiliated allocations to the asset management arm can be assessed as follows: 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 this investment boosts its performance by 1.1% in that year. Using estimates from Del Guercio and Tkac (2002), this boost in performance translates into an incremental \$0.2 million in management fees for the affiliated funds that receive allocations in an IPO (we provide details of our calculations in the Supplementary Material). Using a decay factor of 66% and a discount rate of 10.8%, the present value of this increment in management fees amounts to about \$0.46 million.

Turning now to the impact of kickbacks from affiliated allocations, Goldstein et al. (2011) report "abnormal commissions of between 2.66¢ and 3.54¢ for every \$1 left on the table." We believe this interval is also a reasonable estimate in our context: The evidence in Figure 8 indicates that there is no change in the percentage of allocations to independent funds at the 3-year cutoff, and our stylized model suggests that the same should be true for allocations to favored investors. To remain conservative, we use the lower value in the Goldstein et al. (2011) interval. The impact on kickbacks because of supernepotism then comes to $0.0266 \times 11 = \$0.29$ million.

Overall, the loss in underwriting fees because of supernepotism is \$0.73 million, compared with the combined benefits to management fees and kickback revenues of \$0.46 million + \$0.29 million = \$0.75 million. While these are rough estimates, they suggest that our estimate of the additional underpricing because of affiliated allocations is reasonable.

V. Robustness Checks

The advantage of the RDD methodology is that it offers internally valid identification. The disadvantage is that it might lack external validity because its estimates are local to complier IPOs around the 3-year cutoff. For robustness, we follow Gathergood, Guttnam-Kenney, and Hunt (2019) and complement our RDD evidence with an OLS regression using the full sample of eligible IPOs. Results are reported in Table 4, using robust standard errors for inference.

Our affiliated allocation measures have a positive and statistically significant coefficient in all specifications. This positive correlation persists after controlling for issuer and issue characteristics, as well as year, industry, and underwriter fixed effects.

We performed several other robustness checks. First, we find that our RDD results are not driven by rounding down the age variable (Dong (2015)). Second, they are similar to a subsample of 33 IPOs for which we know the exact founding day (even though the statistical significance is reduced, because of the small sample size). Third, they are similar if we restrict the analysis to allocations to funds affiliated with the lead underwriters. Fourth, they hold within industries and

TABLE 4

OLS Regression of Underpricing on Affiliated Allocations

Table 4 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 1,086 eligible IPOs in the period 2001–2013. Columns 2, 3, 7, and 8 introduce IPO level control variables, as defined in Appenidx Table B1. Columns 4 and 9 introduce year and industry fixed effects. Industry fixed effects are based on the Fama–French 12-industries classification. Columns 5 and 10 introduce lead underwriters' control variables. Returns and fractions are expressed as percentages. All non-dummy variables except *Age* are winsorized at the 2.5% level. Heteroscedasticity-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	1,086	1,086	1,086	1,086	1,086	1,086	1,086	1,086	1,086	1,086

subperiods. Fifth, they hold when using different winsorization thresholds. Sixth, they are stronger if we exclude from our sample the IPOs with uncertainty around their non-compliance with rule 10f-3. See the Supplementary Material for more details.

VI. Conclusion

We identify an unexplored conflict of interest in IPOs and argue that it contributes to IPO underpricing. We hypothesize that underwriting banks may underprice IPOs to benefit their affiliated funds (the "supernepotism" hypothesis). Using rule 10f-3 of the U.S. Investment Company Act, we construct a hand-collected data set of IPO allocations received by funds affiliated with the underwriter. To assess the causal effect of affiliated allocations on the IPO offer price, we implement a fuzzy regression discontinuity design (RDD). We exploit a regulatory threshold, set by rule 10f-3, which provides exogenous variation in the allocation decision. We find that a 1 percentage point increase in allocations to affiliated funds causes underpricing to be 5.4 percentage points higher, resulting in an additional $11 million left on the table. Our evidence suggests that supernepotism has real costs for the issuing firm.

Other conflicts of interest faced by IPO underwriters have long been documented. For example, it is well-known that underwriters allocate underpriced shares to favored investors in exchange for kickbacks in the form of trading commissions. One might expect the supernepotism conflict to mitigate, or be tempered by, these other conflicts; after all, there are limits to how much an underwriter can underprice an IPO, as well as limits to how many shares it can allocate in a self-serving manner. Our findings suggest, however, that the conflicts of interest faced by IPO underwriters may instead reinforce each other. When the underwriter can allocate shares to affiliated funds, the winner's curse faced by regular investors becomes more acute. Favored investors benefit even more from underpriced shares, generating more kickback revenues for the underwriter.

Our findings shed light on a previously unexplored tradeoff facing IPO issuers. For them, the benefits of going public must be compared with the lost IPO proceeds because of supernepotism. Our conversations with asset managers suggest that the supernepotism behavior we document, and its consequences for IPO pricing, are known to some participants in the IPO market, but it is not clear to us whether this behavior is widely known to IPO issuers. Conceivably, an IPO issuer concerned about supernepotism could turn to an underwriter who is less active in the fund management business, but we have no indication, even anecdotally, that this is the case. An intriguing possibility is that IPO issuers may view the underwriter's dumping ground incentive as an offsetting virtue to supernepotism: An issuer might accept the risk of losing proceeds because of supernepotism, if that risk comes with a guarantee that the underwriter will use its own funds to place the issuer's shares and will guarantee a successful offering when market conditions deteriorate.

Overall, the funds affiliated with banks involved in underwriting an IPO receive two benefits: i) Underwriters underprice IPOs more when they expect their affiliated funds to receive IPO shares and ii) 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 to IPO issuers from a conflict of interest faced by banks involved in both IPO underwriting and asset management.

Appendix A. Downloading and Parsing N-SAR Filings

The 77o item of the N-SAR filing asks if the filer was involved in any affiliated transactions pursuant to rule 10f-3. If the answer is yes, then the filer has to provide an attachment containing additional information about each transaction. We downloaded from the SEC EDGAR database the 104,207 N-SAR forms filed from Jan. 2001 to

Dec. 2014. Because an N-SAR form filed in year X can contain information about year X-1, this time span covers the affiliated transactions executed in the period 2001 to 2013. Institutions were instructed to name their attachments “EX-99.77O 10f-3 RULE.” However, since a non-negligible number of attachments were filed with a wrong or incomplete name, 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 any attachment the string “077 O000000 Y”;
- contain in the main form or any attachment the string “10f”;
- contain in the main form or any attachment the string “77o.”

Under these criteria, we keep many false positives that do not contain a 10f-3 attachment. Our objective is to minimize false negatives, so as to lose the least possible information.[20] 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 10f-3 attachment to an N-SAR filing.

FIGURE A1

Example of a 10f-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?
```

[20]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.

Although 10f-3 attachments report information about both equity and bond issues, we hand-collect information about equity issues only. Sometimes the N-SAR filings explicitly distinguish between the two categories; most of the time, however, we have to infer the kind of security issued. For bond issues, the 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; and the reported offer price is typically close to 100 for bond issues, and so forth. When no such information is provided, and we are unable to distinguish equity from bond issues, we include the observation in our data set to minimize false negatives.[21] 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 subportfolio of a fund, or an investment management company.

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

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

Some 10f-3 attachments contain missing values. Notably, the amount of shares allocated to affiliated funds is missing for about 5% of the observations, before any data 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 with underwriter j is missing in one filing, but we observe the total number of shares W allocated to the adviser of fund f and other filings report the individual number of shares m received by other funds with the same adviser, then 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%. Because of these missing allocations, 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.

[21]False positives are lost when we match our 10f-3 data with the SDC database, and so do not constitute a problem.

Appendix B. Variable Definitions

TABLE B1

List of Variables

Table B1 lists and defines all the variables used in this article.

Variable	Description
Ipo Variables	
Underpricing (%)	(first-day closing price − offer price) × 100/offer price
Age (years)	Age of the issuer in years, computed as: issue year − founding year
Proceeds ($ million)	Total proceeds from the issue, in millions of dollars
Assets ($ million)	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 is equal to 1 if all the shares issued are primary shares
Nasdaq	Dummy variable is equal to 1 if the IPO is listed on the NASDAQ
Foreign	Dummy variable is equal to 1 if the issuer is located outside the United States
VentureCapitalBack	Dummy variable is equal to 1 if the IPO is backed by a venture capitalist
LengthIPOprocess (months)	Length of the IPO process in months, computed as: (issue date − filing date)/30.4375
HighRankDummy	Dummy variable is equal to 1 if at least one underwriter has a Ritter ranking equal to 9
NumberLeadManagers	Number of book-runners and lead managers in the syndicate
NumberSyndicateMembers	Total number of syndicate members
GrossSpread (%)	Gross underwriters' spread
FirmCommitment	Dummy variable is equal to 1 if the securities are issued under a firm-commitment contract
Allocation Variables	
AffiliatedAllocPerc (%)	Percentage of the issue allocated to affiliated funds
AffiliatedAllocDummy	Dummy variable is equal to 1 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

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S002210902400053X.

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