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Political connections and IPO underpricing: An efficiency problem

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Abstract

We frame IPO pricing as an efficiency problem for prospective issuers and explore the effect of connections formed via lobbying and PAC (Political Action Committee) contributions. We develop an approach of general application in finance, where relationships of influence are suspected. Rather than imposing a regression-based framework, we allow relationships to manifest themselves in a data-driven manner. Our analysis reveals nonlinearities between IPO pricing efficiency and the two contribution avenues (justifying the fully nonparametric treatment). We are able to uncover relationships separately according to business sector, which we interpret in terms of varied competitive environments.

JEL classification: C6; G10 ; G14 ; G39.

Keywords: IPO underpricing; political connections, PAC and lobbying contributions; data envelopment analysis.

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I. Introduction

In 2014, Google surpassed Goldman Sachs in both lobbying and PAC (Political Action Committee) contributions[2]. Given the bank's historic ties with government, this news drew considerable attention from the press. However, Google had initiated its Washington strategy a decade earlier, just a few months before its IPO (Initial Public Offering) in August 2004. Likewise, other corporate issuers exert great effort to develop their political networks early, opting for a highly discretionary expense during a period of cash scarcity. While few would argue against the long-term benefits of staying in the good graces of politicians, this observed behavior begs the question of whether incremental benefits accrue from the decision to proceed to an IPO 'connected'.

On balance, the odds of attaining a good pricing outcome rarely favor the issuer. The disparity in bargaining power versus the lead underwriter and the liability of newness (Stinchcombe (1965)) result in the systematic dwarfing of the IPO offer price by first aftermarket close. The economic implications are colossal: over the period 1980-2014 alone, a total of 8,060 U.S. issuers realized an average first-day return of 18.6%. In dollar terms, the amassing of $805.8 billion in equity capital entailed an opportunity cost of $149.8 billion[3].

A politically connected issuer may be at an advantage compared to other IPO issuers for several reasons. First, the firm is in less need of an underwriter's reputation for the purpose of certification (Carter et al. (1998)). Shares of an issuer known for its political ties should be easier to sell, obviating much of the marketing burden. Indeed, the increased publicity accompanying elite clientele adds to an underwriter's own reputational capital, so that prestige spillovers cease to be

[2] According to data from the Center for Responsive Politics (CRP), a non-profit U.S. research group, during 2014 Google spent $ 16,830,000 and $ 1,036,926 for lobbying and PAC contributions, respectively. Over the same period, Goldman Sachs was associated with a lobbying expenditure of $ 3,460,000 and PAC of $ 1,017,100.

[3] We rely for these estimates on data from Jay Ritter's website.

unidirectional. Second, politically involved firms have been shown to enjoy preferential access to debt financing (Faccio (2006), Boubakri et al. (2008), Houston et al. (2014)) and so these issuers encounter neither time nor liquidity constraints but instead they can afford to withhold listing until a satisfactory valuation arises. Third, connections mitigate the ex ante uncertainty surrounding a firm's intrinsic value by indicating a capability to extract economic rents or, at a minimum, protection against tail risk. This implicit assurance may replace a low offer price as a means of disseminating confidence in future prospects (c.f. signaling studies such as Allen and Faulhaber (1989), Welch (1989), Chemmanur (1993)).

Intangible assets such as a firm's political network are difficult to identify and cumbersome to model, with incremental information hidden in nonlinearities. We investigate a prospective issuer's potential to retain a larger portion of the surplus value created at an IPO, using lobbying and PAC contributions as proxies for corporate political connections. However, the challenge lies in defining a setting that caters appropriately to the different types of connectedness that they lead to. In this respect, a method allowing relationships to manifest themselves in a data-driven manner would clearly be advantageous**.** Accordingly, we approach IPO pricing as a production problem to be treated in a fully nonparametric procedure. Central to this framing is issuers' ability to minimize underpricing across a variety of settings. Our estimation strategy is twofold, with each stage offering solutions to shortcomings in the literature.

First, prior to examining the influence of exogenous factors, we address the problem of comparability among IPO returns which stems from the fact that returns do not account for price levels[4]. Gondat-Larralde and James (2008, p.449) stress the absence of a theory both explaining

[4] For example, consider two IPOs: IPO A with an offer price of $2 and an aftermarket close of $4; IPO B with an offer price of $10 and an aftermarket close of $20. Because both cases yield an initial return of 100%, the focus on underpricing conceals the disparity in absolute price appreciation (i.e. $2 and $10 for IPOs A and B, respectively) providing no information on whether the issue is 'cheap' or 'expensive'. Consequently, in terms of relative performance assessment, each IPO misleadingly appears to be an appropriate benchmark for the other.

IPO underpricing in equilibrium conditions and determining the average differences of IPO returns on the observed scale. As a consequence, some researchers (inter alia Benveniste and Spindt (1989), Benveniste and Wilhelm (1990)) analyze IPO underpricing without taking into consideration the variation of the phenomenon while others pre-assume its existence (Loughran and Ritter (2002), Ljungqvist and Wilhelm (2005)). Unlike these studies, we introduce a method for establishing comparability without ascribing a direction (underpricing or other) a priori. This is a deterministic frontier approach utilizing the ratio of IPO offer price to first aftermarket close in order to construct non-parametric piece-wise surfaces over the sample. The aim is to envelop the data in the smallest or tightest fitting convex cone, whereby the upper boundary of the fit reveals the optimal practice (Kumar and Russell (2002)). In this case, the emerging empirical frontier is anchored in the best performing issuers, thus setting reliable benchmarks across the sample. For the purpose of the envelopment, we use the mathematical programming technique data envelopment analysis (DEA), which features widely in Operations Research (Charnes et al. (1978), Banker et al. (1984), Sherman (1984), Mahajan (1991), Duzakin and Duzakin (2007), Sueyoshi and Goto (2009), Demerjian et al. (2012)). Demonstrating its extension to IPOs, we develop efficiency scores measured as the output-based distance from the top performers[5] (IPOs that need to be emulated). On this relative basis, we quantify issuers' ability to reduce underpricing across industries, eliminating the methodological challenges laid out in Gondat-Larralde and James (2008).

Our second (and ultimate) task is to assess the effect of a firm's political strategy on the estimated efficiency. Most relative nonparametric efficiency studies (also called two-stage DEA studies) in Operations Research derive efficiency levels in the first stage and, subsequently, employ a regression-type framework (Tobit, OLS models, etc.) in order to explain observed variations

[5] The measurement of productive efficiency has been well-developed in the seminal works of Farrell (1957), Aigner and Chu (1968), Afriat (1972), Aigner et al. (1976), Färe and Lovell (1978), Forsund et al. (1980) and Kopp (1981).

(dependent variable) based on the exogenous terms (control variables)[6]. However, this route imposes unrealistic assumptions on the data-generating process leading to biased results (Simar and Wilson (2011)). In order to avoid such misspecifications, we apply the probabilistic method of efficiency estimation (Daraio and Simar (2005, 2007)) alongside the latest developments (Bădin et al. (2012)) on the impact measurement of environmental factors. Consequently, we carry forward our second stage analysis in a completely nonparametric framework without relying on modeling assumptions which may not be supported by the data. This approach enables us to capture all potential nonlinearities in the relation between IPO returns and lobbying and PAC intensity. Apart from this benefit, the shift of focus from outcome prediction to efficiency evaluation renders our estimates immune to endogeneity[7], a common source of bias in the IPO-return equation which can also arise from firms' self-selection into political contributions.

In order to conduct this work, we require a new and comprehensive database. We manually investigate U.S. IPO deals recorded in the Securities Data Company (SDC) database over the period from 1998 to 2014 for evidence of political contributions within the 12-month period prior to the issue day. This search involves scrutiny of two distinct sources. The data on PAC contributions come from the files of the Federal Election Commission, whereas for lobbying contributions we search the electronic archives of the Center for Responsive Politics (CRP). After merging the contributions databases with Center for Research in Security Prices (CRSP) data on aftermarket prices, we identify 379 unique IPOs which have exhibited either type of activity. These firms cover 12 out of the 14 Thomson Reuters proprietary macro-level industry classifications.

[6] Refer to Simar and Wilson (2007, 2011) for an excellent analysis of the relevant studies.

[7] Also, as in Black and Smith (2004) and Frölich (2008), nonparametric estimators overcome the problems associated with endogenous control variables and remain consistent in lieu of instrumental variables.

Our results do, indeed, reveal nonlinearities in the relationship of efficiency with the two contribution avenues (in itself justifying the fully nonparametric treatment) and, moreover, the relationship differs across business sectors. By and large, PAC contributions conform to their hypothesized role in reducing the amounts of money left on the table by prospective issuers. Market participants factor in direct, interpersonal relationships with policy makers. Evidence from lobbying contributions corroborates this conclusion. The majority of IPOs exhibiting efficiency take advantage of both lobbying and PAC contributions. Results for the complete dataset show lobbying versus IPO efficiency as an inverted "U"-shape which, however, changes to a "U"-shape when data are restricted to IPOs with positive returns that lie on the empirical frontier and are, therefore, efficient. The change in shape prompts a closer examination, combined with the thought that firms across the various economic sectors are likely to pursue heterogeneous political objectives. We compare Energy and Power, Financial, and Industrial sectors and find different (plausibly "strategically tailored") spending. Lobbying contributions in Energy and Power account for a positive nonlinear effect on IPOs' efficiency levels, whereas PAC money appears to erode value. This may be explained by a heavy regulatory framework demanding quality communication between those setting policy and those affected by it. The reverse is observed in the Industrial sector, from which we surmise that PAC campaigns, as a superior means for networking, cajole decision makers into government purchases and favorable appropriations from the Federal budget for the industry. The Financial sector, in contrast, barely shows an economically meaningful association of either lobbying or PAC with IPO efficiency levels, perhaps because it already exerts a political role by virtue of its centrality to the economy.

The remainder of the paper proceeds as follows. Section II provides a review of the relevant literature and develops our main conjecture. Section III describes database assembly and illustrates the proposed methodology. The empirical analysis is in Section IV. Section V offers a discussion

and possible interpretations of key findings. We subject our results to additional robustness tests in Section VI. Section VII concludes the paper.

II. Background and hypothesis development

A. Proximity to politics as a value-adding element

Political connections may be formed via sourcing managers and key executives who are well-connected themselves or through the corporate treasury for political contributions. International evidence traces connections from interpersonal networks into firm value. Fisman (2001), for example, documents the share price of connected firms in Indonesia swinging in line with news of President Suharto's health. Faccio (2006), exploring the interplay of business and politics in 47 countries, lists benefits for organizations employing officials with an alleged political footprint. Specifically, connected firms are capable of maintaining larger market shares as well as bearing more leverage compared to their non-connected peers. An additional privilege comes in the form of systematic tax discounts. Notably, the greater the observed extent of connectedness, the more these features emerge. Faccio and Parsley (2009) follow the market reaction of firms headquartered in politicians' hometowns in 36 countries subsequent to their unexpected death announcements and find a 1.7% decline in value across a wide spectrum of political and economic conditions, including the U.S.

The bourgeoning Chinese IPO market, in conjunction with the high degree of interconnectedness between local businesses and the central government, has stimulated research on implications for newly listed equities. The limited underpricing of politically connected firms features in this literature. For instance, Fan et al. (2007) note the role of CEOs' links with government as both an asset during the IPO day (exactly because of the constraining effect on return) and a liability significantly impairing firms' growth and earnings prospects over the long-run. In a similar spirit, Francis et al. (2009), using multiple proxies of political connections

(directors' network, type of state ownership, and underwriter's ability to attract revenue from state-owned companies), corroborate the relationship with underpricing. Additionally, they associate connected issuers with larger P/E ratios and higher IPO offer prices so that proximity to politics emerges as a pivotal factor in raising greater amounts of capital. Of course, using the Chinese capital markets as laboratories for assessing the effect of political connections on IPO underpricing invites controversy. On the one hand, the peculiar economic model of China cripples the transferability of findings to a mature Western market setting. On the other, it may be argued that if the effect is capable of manifesting itself in spite of the constant demand for Chinese equities, then a stringent robustness test has already been fulfilled.

U.S. evidence tracing connections that stem from political contributions also reports significant implications for firm value. Cooper et al. (2010) study the correlation of PAC contributions with the cross-section of future abnormal returns and document a positive association. Chen et al. (2015), substituting PAC data for lobbying, corroborate this relationship. In parallel, the authors complement market measures of performance with accounting elements such as net income and operating cash flow, thereby showing the effect permeates into firm fundamentals. The value-enhancing element of contributions can equally manifest itself via the advancement of more dubious purposes. Thus, Yu and Yu (2011) attribute to firms remaining active in lobbying an interesting immunity from fraud detection. In particular, scrutiny by the relevant authorities lags by an average of 117 days while violators are 38% less likely to be held accountable for fraudulent actions in the first place. Similarly, Correia (2014) highlights the role of both lobbying and PAC contributions as powerful deterrents against SEC enforcement actions.

B. Political connections in the process of going public

Following the research of Stoll and Curley (1970) and Logue (1973) registering positive skewness of the IPO returns distribution, underpricing is frequently framed as a balance among

conflicting incentives of the principal IPO participants. With underpricing arising from informational asymmetries, firms may forego some of the wealth created at the IPO by setting a lower price in an attempt to mitigate ex ante uncertainty. This behavior conforms to a signaling model and differentiates quality firms from other issuers (Allen and Faulhaber (1989), Welch (1989), Chemmanur (1993), Jegadeesh et al. (1993)). In parallel with transmitting assurances matching their standing, issuers themselves require market feedback and predictions of demand. Sophisticated investors, mainly in the form of institutional investors, can be central in this respect. Therefore, a number of studies establish underpricing as a means of deferred compensation for information revelation (Benveniste and Spindt (1989), Benveniste and Wilhelm (1990), Spatt and Srivastava (1991), Sherman and Titman (2002), Cornelli and Goldreich (2001, 2003)). Ritter and Welch (2002) speculate that IPO subscription may be used as a tool for exerting influence on politicians, though they do not provide further evidence.

A politically involved issuer is equipped to reduce the uncertainty surrounding an IPO. The connections formed via political donations can structure a network which facilitates information flow such as the exchange of issuer-specific information for forecasts of demand and market sentiment. To the extent that proximity to politics evidences a firm's capability to extract economic rents, there is less disagreement on the value of connected firms, thereby eliminating the need to signal quality via a low offer price.

In parallel, political connections reinforce an issuer's bargaining position in pricing negotiations with the lead underwriter. Rather than the issuer gaining benefits in prestige from the underwriter for legitimacy, this may be reversed; a feature especially desirable if the underwriters' market structure conforms to a model of oligopolistic competition (Loughran and Ritter (2004), Liu and Ritter (2010)). The immediate prestige spillovers do not preclude long-run expectations of a recurring stream of revenue in the form of new issuance activity, business with the brokerage division and potential M&As. Conversely, connected firms have been associated with advantageous

access to alternative means of financing such as bank loans (Houston et al. (2014)). Attaching less urgency to the IPO funds, therefore, the issuer is able to negotiate a higher valuation. As a result, the underwriter is incentivized to exert greater effort to retain a connected client at a time when the latter is able to be selective.

C. Lobbying and PAC: two distinct means for establishing connections

Lobbying and PAC contributions constitute a firm's primary vehicles for gaining access to the U.S. political system. To put this endeavor in perspective, 2014 saw a reported aggregate lobbying expenditure of $ 3.21 billion, whereas PAC contributions over the election cycle fell slightly short of $ 0.5 billion. The disparity in magnitudes is indicative of their different natures.

Lobbying aims to sway politicians to interventions that advance corporate interests. This may equally translate into refraining from action in cases where the optimal outcome lies with the status quo (defensive lobbying). The process is more elaborate than an exchange of money for political favors and constitutes an important input in the making of politics. The Lobbying Disclosure Act of 1995 (LDA) defines as a lobbying contact any oral or written interaction (inclusive of electronic communications) to an executive branch official or a legislative branch official made on behalf of a client with regard to the formulation, modification, or adoption of federal laws, executive orders, or government contracts, etc. As a communications endeavor, therefore, lobbying represents a valuable source of information for legislators, even more so for issues of an especially technical character. In-house or external specialists, commonly former Congress members themselves, spearhead the lobbying effort and attempt to pinpoint elements in proposed legislations which confer utility on more stakeholders (inclusive of the affected political constituencies) than the client firm. With the relevant research (see Leech et al. (2005), Baumgartner et al. (2011)) showing that salient issues demand frequent and targeted campaigns, corporate lobbying has more than doubled since 1998, the first year for which lobbying data are

available in databases following the LDA. In the absence of a legal cap, firms' expenditures far exceed what is required for staff compensation and related overhead in order to cater to an increasing variety of incumbent politicians' private expenses (e.g. travel expenses, meals and events organization). The cash flows are disclosed, at an aggregate level only, on standardized lobbying reports and identified by their subject matter, also designated as 'lobby issue'.

PAC are commonly formed by corporations and special interest groups in order to support or sabotage the election of a specific candidate. Revolving around legislators rather than the legislative process, PAC contributions offer a firm first-order connections with people in power. This element of directness differs from lobbying, where a firm derives connectedness through lobbyists' proprietary networks and relinquishes it by termination of the campaign. Additionally, PAC impose substantial limitations on contribution size and donors' identity. In particular, even though corporate cash is eligible to cover a PAC's operating costs, contributions beyond the break-even point should be sourced from third-party donors. To this end, firms routinely solicit financing from principal constituents such as directors, employees and their families and, given that no individual may exceed the legal ceiling of $5 thousand, mass participation becomes a matter of vital importance to a campaign's success.

Firms select between the two contribution types based on their competitive environment and organizational idiosyncrasy. Large establishments which often attract public scrutiny (and increased litigation costs) are strongly incentivized to craft legislation on a bill-to-bill basis. In this respect, lobbying is essential. As an added benefit, campaign costs are a smaller consideration since they can be spread over an extended asset base. Market concentration has also been shown to relate positively to lobbying (e.g., Zardkoohi (1985)); conceivably, the fewer the participants in an industry, the larger the portion of the anticipated benefits that accrue to the donor firm as opposed to free-riders. To the extent that firms emphasize proprietary rights protection and securing concessions on the development of novel technologies, R&D intensity is another plausible factor for

lobbying. Similarly, a heavy regulatory framework induces a firm to communicate its perspective to legislators. Conversely, PAC campaigns facilitate firms with a large percentage of unionized employees or a heavy reliance on government contracts as a superior means for networking and claiming favoritism on an interpersonal basis. Of course, this does not preclude the intrusion of non-economic factors into the PAC decision such as fads, internal politics, social norms and peer demand.

Lobbying may be framed as a conduit of information and PAC as an open reference for the entity transmitting this information, the two complementing one another (Langbein (1986), Wright (1990), Humphries (1991), Austen-Smith (1995), Milyo et al. (2000), Ansolabehere et al. (2002)). Langbein (1986) conducts surveys of legislators and their cabinets and finds that the former appropriate time to lobbyists according to the PAC intensity of their client firms. Milyo et al. (2000) go a step further by refuting altogether the influence potential of PAC. Instead, the authors reduce these campaigns to simple entry tickets for access and dialogue on an ad hoc basis. Formally, the symbiotic relationship is designated as the 'access-influence' hypothesis. Adhering to this framing, in developing the main conjecture in our study, we group both contribution types under the umbrella of political connections.

III. Data and methodology

Next, we describe the assembly of our database and how we construct a model in order to extract effects on IPOs without imposing a regression-based framework, allowing relationships (linear or otherwise) to arise from the data.

A. Data

Following the Lobbying Disclosure Act of 1995, databases are available covering lobbying activity from 1998. We retrieve the population of U.S. IPOs for the period January 1, 1998 to

December 31, 2014 from the Securities Data Company (SDC) database. In line with the majority of IPO studies, we exclude deals with an offer price smaller than $5 per share (penny stocks), reverse LBOs, limited partnerships, American depositary receipts (ADRs) and foreign-based firms whose shares may already trade in their home markets. We eliminate real estate investment trusts (REITs), closed-end funds, royalty trusts and other special purpose investment vehicles. For this purpose, we exclude all SIC codes within the interval 6723-6999, inclusively. Special caution is exercised to identify and eliminate IPOs which, while bypassing Thomson Reuters' closed-end fund filter, still function in this manner. The last restriction involves corporate spin-offs; these IPOs have only recently acquired organizational autonomy from a mature and sizeable organization so that the reputation of the mother firm largely certifies the offering, alleviating a significant portion of the ex-ante uncertainty. These interventions leave us with a sample of 379 unique IPOs.

The pricing data come from two distinct sources. While SDC is an excellent source for IPO offer prices, its coverage significantly deteriorates when it comes to aftermarket prices. For first trading day closes, we rely on the Center for Research in Security Prices (CRSP) and match the two databases. The sources for political contributions similarly diverge. We manually search each IPO company in the electronic platform of the Center for Responsive Politics (CRP) for evidence of lobbying activity. CRP sources data straight from the semi-annual lobbying reports submitted to the secretary of the Senate's Office of Republic Records (SORP). The PAC contributions are retrieved from the archives of the Federal Election Commission (FEC) where we reiterate the investigation for all IPOs in the sample. Notably, in cases of multiple lobbying or PAC activity, we consider the contributions exhibiting the closest time proximity to the issue date for plausibly dominating in value relevance over older cash flows. Thus, we assemble a new and comprehensive database of U.S. firms' political standpoint at the time of their transition into the public domain.

B. Sample description

Our dataset consists of 379 U.S. IPOs, 317 of which are underpriced and 62 are overpriced (refer to Table 1 for descriptive statistics and IPO identification by sector). In order to reinforce the robustness of our results, we seek in all of the analyses separate evidence from both the full and underpriced samples.

Table 1
Summary statistics and IPO sample description

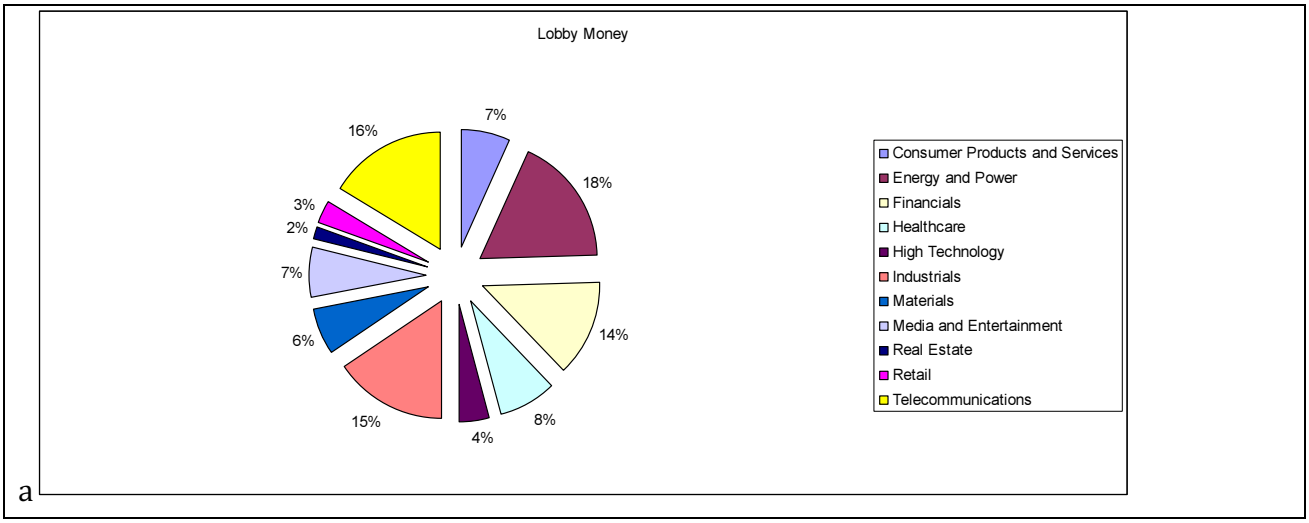
Our sample consists of 379 U.S. IPOs for the period January 1, 1998 to December 31, 2014 extracted from the Securities Data Company (SDC) database. IPOs with an offer price smaller than $ 5 per share (penny stocks), reverse leveraged buyouts, limited partnerships, American depositary receipts (ADRs), foreign-based firms, real estate investment trusts (REITs), closed-end funds, royalty trusts and other special purpose investment vehicles are excluded from the sample. The issuing firms have been manually investigated in the electronic platform of the Center for Responsive Politics and the archives of the Federal Election Commission for evidence of lobbying and PAC contributions, respectively. All figures are in 12/2014 U.S. dollars. We rely on the SDC database for IPO offer prices, whereas aftermarket prices are sourced from CRSP. The lower part of the table distributes the IPOs across the 12 (out of 14) Thomson Reuters' proprietary macro-level industry classifications which we have been able to associate with political expenditure.

Variable	Mean	Median	Std Dev	Minimum	Maximum	*N*	Percentage (%)
Offer price	17.29	16.00	8.81	5.00	97.00		
1st close	21.56	18.11	18.55	5.00	280.00		
Lobby money	279,268	80,000	788,021	0.00	9,570,000		
PAC money	26,292	0.00	84,326	0.00	780,000		
High Technology						78	21
Healthcare						72	19
Financials						49	13
Energy and Power						27	7
Materials						27	7
Industrials						33	9
Consumer Products & Services						27	7
Media and Entertainment						17	4
Retail						14	4
Real Estate						3	1
Telecommunications						21	6
Consumer Staples						11	3
Total						379	100

Figure 1 presents an overview of the percentages of total lobbying and PAC activity on a sectoral basis. In particular, subfigure 1a reveals that companies from the Energy and Power, Telecommunications, Industrials and Financials sectors account for the highest percentages of lobbying. Similarly, subfigure 1b indicates that the largest PAC donations come from companies operating within the sectors of Energy and Power, Industrials, Financials and Media and Entertainment. Conclusively, the Energy and Power, Industrials and Financials sectors allow almost equally for lobbying and PAC. However, preferences towards either spending manner can exist. For example, the Media and Entertainment sector donates primarily PAC money, whereas the Telecommunications sector is more heavily involved into lobbying.

Figure 1
Distribution of lobby and PAC money per sector

Subfigure 1a presents the per sector percentages of lobbying contributions made by 379 U.S. IPO firms over the period January 1, 1998 to December 31, 2014. Subfigure 1b presents the respective percentages for PAC money.



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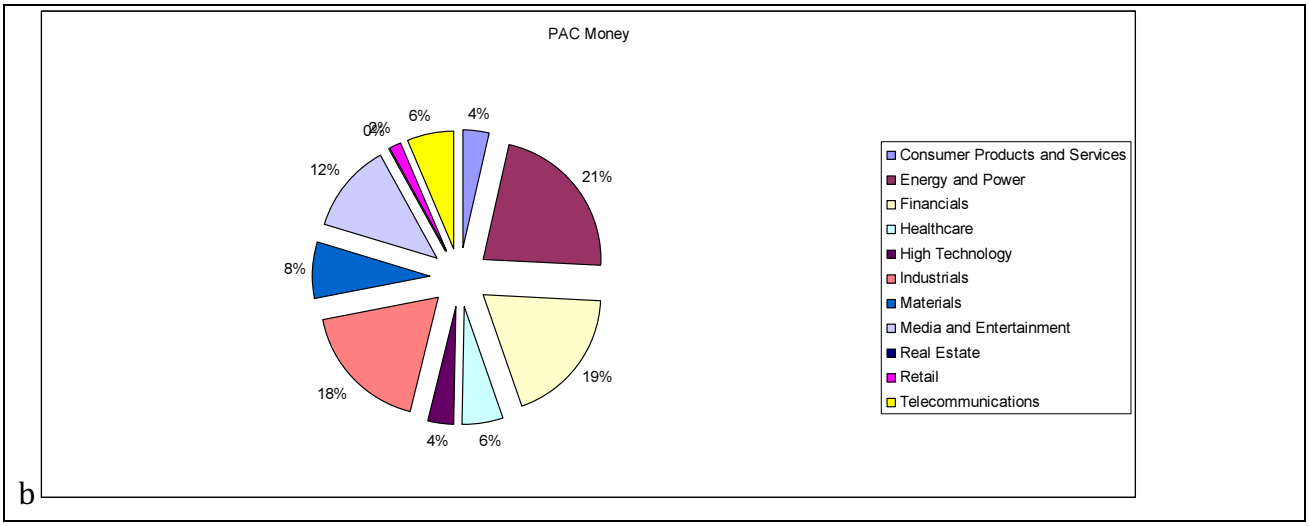


C. Methodology

1. The model

Suppose that an issuer's ability to evaluate an IPO can be characterised by the pairs of the first aftermarket closing price $e \in \Re_+^p$ and the IPO offer price $b \in \Re_+^q$. Then the process of the issuer's evaluation of the IPO can be characterised by the activity set Ω which is the support of the density of (E, B) defined as:

(1) $$\Omega = \left\{ (e,b) \in \Re_+^{p+q} \,\middle|\, f_{EB}(e,b) > 0 \right\},$$

where f_{EB} is the joint density of (E, B) with the probability function H_{EB} defined as:

(2) $$H_{EB}(e,b) = P(E \le e, B \ge b).$$

From (1) and (2) we may then write:

(3) $$\Omega = \left\{ (e,b) \in \Re_+^{p+q} \,\middle|\, H_{EB}(e,b) > 0 \right\},$$

and therefore from (3) we assume free disposability of Ω. Then for any e such that $P(E \le e) > 0$,

(4) $$H_{EB}(e,b) = H_{B|E}(b|e) F_E(e),$$

where $H_{B|E}(b|e) = P(B \ge b | E \le e)$ and $F_E(e) = P(E \le e)$. Then Ω can be defined as:

(5) $$\Omega = \left\{ (e,b) \in \Re_+^{p+q} \middle| H_{B|E}(b|e) > 0 \right\}.$$

Given that the objective of an issuer is to reduce underpricing, we can determine the issuer's performance in evaluating an IPO at price levels (e_0, b_0) following Farrell (1957) as:

(6) $$\phi(e_0, b_0) = \sup\left\{ \phi > 0 \middle| H_{B|E}(\phi b_0 | e_0) > 0 \right\}.$$

Finally, the empirical version of $H_{B|E}$ can be stated as:

(7) $$\hat{H}_{B|E}(b|e) = \frac{\sum_{i=1}^{n} I(E_i \le e, B_i \ge b)}{\sum_{i=1}^{n} I(E_i \le e)}.$$

In the spirit of other studies (Daraio and Simar (2005, 2007), Jeong et al. (2010), Bădin et al. (2012)), let lobbying and PAC money be denoted by $M \in \Re^r$ which are the environmental/exogenous factors influencing the issuer's evaluation process. Given that $M = m_0$, then the conditional process of an issuer's evaluation of an IPO Ω_{m_0} is characterised as:

(8) $$\Omega_{m_0} = \left\{ (e,b) \in \Re_+^{p+q} \middle| f_{E,B|M}(e,b|m_0) > 0 \right\},$$

where $f_{E,B|M}(e,b|m)$ is the conditional density of (E,B) given $M = m$. Then,

(9) $$H_{B|E,M}(b|e,m) = P(B \ge b | E \le e, M = m),$$

And so Ω_{m_0} can be represented as:

(10) $$\Omega_{m_0} = \left\{ (e,b) \in \Re_+^{p+q} \middle| H_{B|E,M}(b|e,m_0) > 0 \right\}.$$

Then the issuer's conditional efficiency score of IPO evaluation (e_0, b_0, m_0) is defined as:

(11) $$\phi(e_0, b_0 | m_0) = \sup\left\{ \phi > 0 \middle| (\phi b_0, e_0) \in \Omega_{m_0} \right\} = \sup\left\{ \phi > 0 \middle| H_{B|E,M}(\phi b_0 | e_0, m_0) > 0 \right\}.$$

2. The empirical estimation

2.1 Data envelopment analysis (DEA)

Grounded in the ideas of Farrell (1957), data envelopment analysis (DEA) is a linear programming formulation that describes a correspondence between multiple inputs and outputs. Unlike a production function which is defined by an equation, the DEA's envelope is data-driven. That is, DEA (and not the researcher) determines which input-output combinations are efficient and thereby shape the efficient frontier. Following the work of Charnes et al. (1978), DEA has been applied in operations management (see Banker et al. (1984), Sherman (1984), Mahajan (1991)) but is largely absent from the finance literature. Some traces can be found in Varian (1990) who argues for a nonparametric approach when measuring the optimal performance of customers, investors and other economic agents. Assigning a lesser priority to statistical significance, Varian holds that the economic significance of a deviation from the optimal behavior entails more relevance. Employing a set of variables (quantities demanded, price and output), he develops metrics relying on residuals which capture the difference of outputs over inputs. Seiford and Thrall (1990) rely on these measures in order to draw a direct link with efficiency scores derived from DEA.

In IPO research, DEA estimation remains in its infancy, which comes as a surprise given the perennial quest in this literature to overcome endogeneity concerns within the underpricing equation. The sole extant study is from Kooli (2006); however, with a theoretical framing that focuses on investors' ability to maximize realized returns on IPO shares, Kooli overlooks the big picture which rests upon the excessive amounts of capital foregone at listing - the decision making units are indicative, with the offer price, number of shares and IPO proceeds comprising the inputs, whereas the first aftermarket price and quarterly return are outputs.

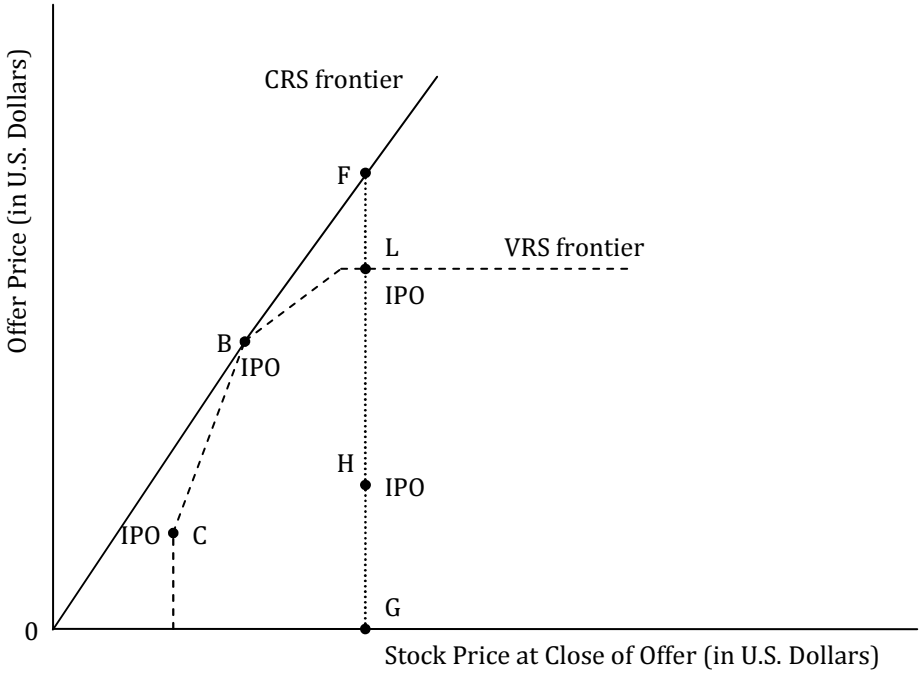
Our approach, in contrast, investigates IPO performance from the issuer's perspective. Given that IPOs are underpriced (Ritter (1991), Jain and Kini (1994), Loughran and Ritter (1995), Lowry et al. (2010)), the performance of an issuer can be evaluated on the basis that the

phenomenon of underpricing is reduced. We can, therefore, apply the nonparametric methodology of DEA in order to measure the efficiency of the issuer's ability to evaluate better an IPO by leaving less money on the table. Figure 2 presents schematically two theoretical frontiers under the constant returns to scale (CRS) and variable returns to scale (VRS) assumptions.[8] The horizontal axis indicates the stock price at close of offer and the vertical one relates to the offer price. Consider four IPOs at points C, B, L and H. The frontier under the assumption of CRS (VRS) is represented by the straight solid (dashed) line. As it can be easily observed, under the assumption of CRS only the IPO at point B is efficient in maximizing the offer price under the stock price at close of offer (i.e. minimizing the underpricing effect). However, when the assumption alters to VRS, the IPOs at points C, B, and L are regarded as efficient. In both regimes, the IPO at point H remains inefficient; under the CRS assumption its efficiency relates to the distance from the observed data point to the CRS frontier and is equal to the ratio of GF/GH. Alternatively, as per the VRS assumption, its efficiency is given by GL/GH. Therefore, in our analysis we need to estimate these distances under the two different technologies.

[8]The CRS assumption is the most common economic assumption and has greater discriminative power compared to the VRS assumption (Zelenyuk and Zelenyuk (2014)). In our case, CRS suggests that a proportionate increase in e results in the same proportionate increase in b. However, under the more flexible assumption of VRS, a frontier may also exhibit increasing and decreasing returns to scale in different regions. Since our sample contains U.S. IPOs from companies operating in different sectors and in different time periods, scale effects can be present and may mask the estimated efficiency levels. Therefore, this study measures IPO efficiency under both the CRS and VRS assumptions.

Figure2
Graphical representation of the theoretical frontiers

The solid line presents the IPOs' theoretical frontier under CRS. The dashed line presents the IPOs' theoretical frontier under VRS. The black dots indicated by the letters C, B, L and H refer to the theoretical positions of hypothetical IPOs. The letters F and G represent distance points.



In order to estimate the radial distances presented in Figure 2, we follow the estimators introduced by Charnes et al. (1978) by implying the CRS assumption (ϕ_{CRS}) and, subsequently, the estimators introduced by Banker et al. (1984) implying the VRS (ϕ_{VRS}) . Both estimators enable us to calculate the model presented in (6) and can be expressed as:

(12) $$\hat{\phi}_{CRS}(e_0, b_0) = \sup\left\{\phi > 0 \middle| e_0 \geq \sum_{i=1}^{n} \gamma_i E_i, \phi b_0 \leq \sum_{i=1}^{n} \gamma_i B_i, \gamma_i \geq 0\right\},$$

(13) $$\hat{\phi}_{VRS}(e_0, b_0) = \sup\left\{\phi > 0 \middle| e_0 \geq \sum_{i=1}^{n} \gamma_i E_i, \phi b_0 \leq \sum_{i=1}^{n} \gamma_i B_i, \sum_{i=1}^{n} \gamma_i = 1, \gamma_i \geq 0\right\}.$$

2.2 Second stage analysis

Subsequently, in order to incorporate the effect of political donations into our measurement (equation 11), we need to adopt smoothing techniques. Therefore, let $I(m_0, h)$ be the indices defined as $I(m_0, h) = \{i \| \|M_i - m_0\| \le h/2\}$. The empirical version of $H_{B|E,M}(\cdot|\cdot,\cdot)$ can be estimated as:

$$\hat{H}_{B|E,M}(b|e,m) = \frac{\sum_{i=1}^{n} I(E_i \le e, B_i \ge b, \|M_i - m\| \le h/2)}{\sum_{i=1}^{n} I(E_i \le e, \|M_i - m\| \le h/2)} = \frac{\sum_{i \in I(m_0,h)} (E_i \le e, B_i \ge b)}{\sum_{i \in I(m_0,h)} (E_i \le e)}, \quad (14)$$

where h is bandwidth applied using the procedure described by Bădin et al. (2010) and based on the least squares cross-validation data driven method (Hall et al. (2004)). The IPO performance from the issuers' point of view taking into consideration the influence of lobby and PAC money can then be written as:

$$\hat{\phi}_{CRS}(e_0, b_0 | m_0) = \sup\left\{\phi > 0 | e_0 \ge \sum_{i \in I(m_0,h)} \gamma_i E_i, \phi b_0 \le \sum_{i \in I(m_0,h)} \gamma_i B_i, \gamma_i \ge 0\right\}, \quad (15)$$

$$\hat{\phi}_{VRS}(e_0, b_0 | m_0) = \sup\left\{\phi > 0 | e_0 \ge \sum_{i \in I(m_0,h)} \gamma_i E_i, \phi b_0 \le \sum_{i \in I(m_0,h)} \gamma_i B_i, \sum_{i \in I(m_0,h)} \gamma_i = 1, \gamma_i \ge 0\right\}. \quad (16)$$

Clearly, the LPs presented in equations 12, 13, 25 and 26 suggest that the IPO efficiency scores are measured on the basis that we try to maximize the IPO offer price given the stock price at close of offer. The above estimators are also called output-oriented DEA models. The choice of orientation is crucial and relies on the pre-investigation of those parameters/variables that the decision maker has greater control over (Coelli et al. (2005)). Since we study IPO performance from the issuer's perspective, the decision maker (that is the issuer) can determine to a larger extent the IPO offer price rather than the stock price at close of offer. Accordingly, the above LPs minimize underpricing by indicating the efficient IPOs with efficiency scores equal to 1 $(\text{i.e. } \hat{\phi} = 1)$. Respectively, the inefficient IPOs assume scores of $0 \le \hat{\phi} < 1$.

As a further step, we apply the latest developments by Bădin et al. (2012). In this regard, we need to create ratios of conditional to unconditional efficiency scores as:

$$\hat{Q} = \frac{\hat{\phi}\left(e_0, b_0 \middle| m_0\right)}{\hat{\phi}\left(e_0, b_0\right)} \tag{17}$$

Then, by using a nonparametric regression we are able to analyze the behavior of $\hat{Q}$ as a function of lobby and PAC money. Let the nonparametric regression smoothing be presented as:

$$Q_i = g\left(M_i\right) + \varepsilon_i, i = 1,...,n, \tag{18}$$

where ε_i is the error term with $E\left(\varepsilon_i \middle| M_i\right) = 0$, and g is the mean regression function, since $E\left(Q_i \middle| M_i\right) = g\left(M_i\right)$. In order to estimate the regression function, we follow Jeong et al. (2010) and apply a local linear estimator which is less sensitive to edge effects. Then, the presentation of three-dimensional pictures will reveal the combined effect of lobby and PAC money on IPOs' efficiency levels. An increasing nonparametric regression will indicate a positive effect; a decreasing one a negative effect. Overall, the adoption of the fully nonparametric approach offers two main advantages. First, it does not impose any prior assumptions on the functional forms of the examined relationships and, secondly, it enables us to reveal any nonlinear relationships.

IV. Empirical results

Figure 3 presents the empirical frontiers for the offer price versus closing price based on the two samples under the CRS and VRS assumptions. In particular, subfigure 3a indicates the empirical frontiers for the full sample (i.e. including overpriced IPOs, N=379); the straight solid (dashed) line represents the empirical frontier under the CRS (VRS) assumption. As expected, overpriced firms have higher efficiency scores and lie on the two frontiers[9]. Since the assumption of

[9]An IPO which is efficient under the CRS assumption is also efficient under the VRS assumption. However, an IPO efficient under the VRS assumption may not be efficient under the CRS assumption.

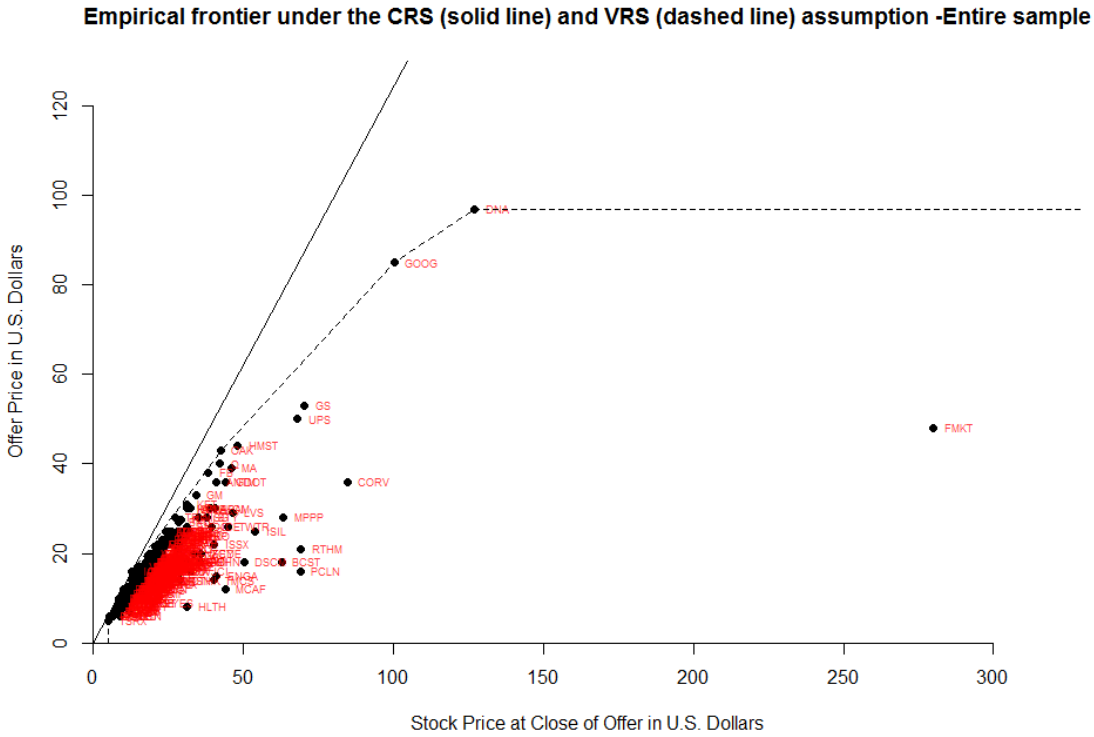
CRS has higher discriminative power than VRS, fewer IPOs are on the CRS frontier. Conversely, under the VRS assumption, we account for scale and heterogeneity effects. As a consequence, more IPOs are deemed efficient and lie on the frontier[10]. Subfigure 3b illustrates the empirical frontiers when overpriced IPOs are eliminated from the sample (N=317). The slope of the CRS frontier becomes considerably smaller compared to the previous CRS frontier (subfigure 3a, which includes overpriced IPOs).[11] Moreover, in this case, we observe that more IPOs lie on both the CRS and VRS frontiers. This, again, is attributed to the exclusion of the overpriced IPOs. Since in our analysis the minimization of underpricing suggests efficiency, the overpriced IPOs envelope the performance of the other IPOs and are always deemed efficient.

[10]The CRS frontier is more robust compared to the VRS frontier and, therefore, fewer IPOs under the CRS assumption are deemed efficient.

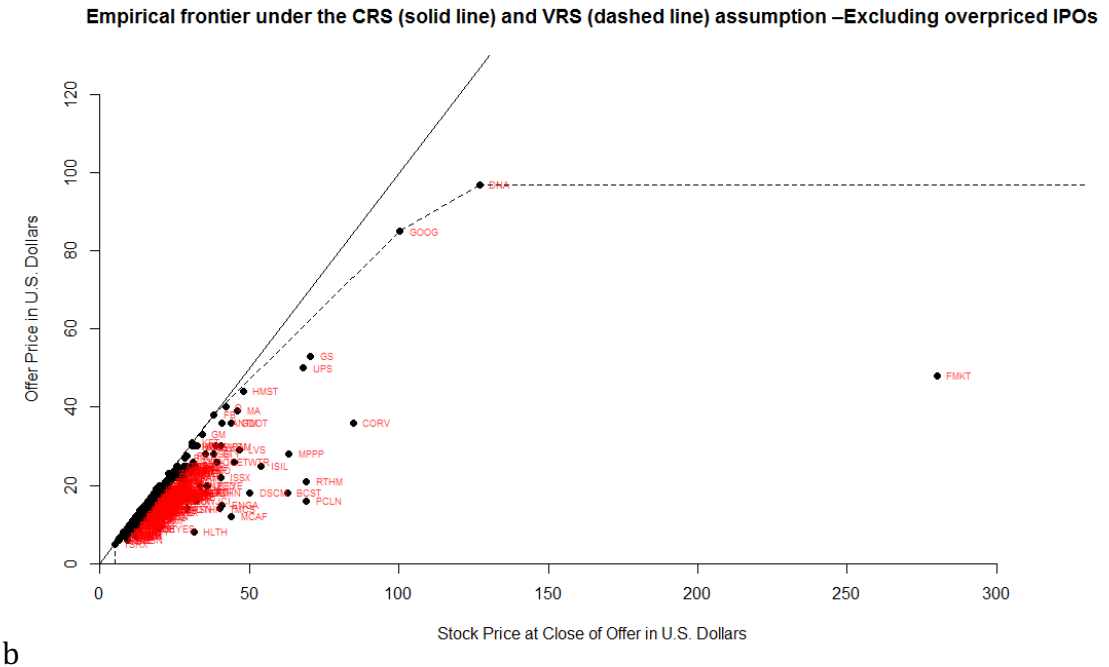
[11]Since in our analysis efficiency is represented by the minimization of IPO underpricing, overpriced IPOs will always be efficient and shape the efficient frontier under both the CRS and VRS assumptions.

Figure 3
Graphical representation of the empirical frontiers

Subfigure 3a presents the estimated empirical frontier for all 379 IPOs in our sample. Subfigure 3b presents the empirical frontier for the 317 IPOs (i.e. we have excluded the overpriced IPOs). The solid line indicates the empirical frontier under the CRS assumption, whereas the dashed line indicates the empirical frontier under the VRS assumption.



a



b

Assessing unconditional efficiency estimates[12] from the full sample, we find that 233 out of the 379 IPOs have efficiency scores above the sample mean (0.706) in the CRS regime. However, under VRS, 222 out of the 379 IPOs exceed the average efficiency score (0.770). Table 2 presents the top and lowest 30 performers under the two regimes. The mean efficiency score of the top group under CRS is 0.8426, whereas under VRS it becomes 0.9556. Furthermore, under CRS, only 1 company is deemed to be efficient; under VRS 6 IPOs have an efficiency score equal to 1. The top 30 performers represent 9 different sectors (Consumer Products and Services, Consumer Staples, Energy and Power, Financials, Healthcare, High Technology, Industrials, Materials, Telecommunications). Among these companies, 11 have donated both lobby and PAC money. Looking at the lowest 30 performers, the mean efficiency score under CRS (VRS) is 0.3804 (0.459). Notably, the majority of these issuers operate in the "High Technology" sector. In this respect, our findings complement evidence by Lowry and Schwert (2002) suggesting that high-technology firms tend to experience higher first-day returns. From our efficiency point of view, because such issuers increase the underpricing effect, they significantly impair their efficiency levels. Finally, we note that these 30 IPOs have mostly donated lobby and not PAC money.

[12]As has been pointed by Bădin et al. (2012) and Mastromarco and Simar (2014), it is not meaningful to examine the classification of decision making units (DMUs) using conditional efficiency estimates since they are obtained accounting directly for the effect of the exogenous variables. Consequently, we present the original efficiency scores. However, all the results obtained are available on request.

Table 2
Efficiency analysis- 379 IPOs: top and worst performers

We present the top and worst 30 IPOs for the full sample (N=379) in terms of their ability to minimize underpricing. We sort the IPOs based on their efficiency performance under the VRS assumption in order to account for differences between sectors. When an IPO is efficient (i.e. efficiency score equal to 1.000) under the CRS assumption, it is also efficient under the VRS assumption. Additionally, we identify the IPO firm's sector alongside with the lobby and PAC donation amounts. The main descriptive statistics for the efficiency estimates, lobby and PAC amounts are tabulated below each IPO group.

Listing Date	Company	Ticker	CRS	VRS	Lobby Money	PAC Money	Sector
07/29/2014	ContraFect Corp	CFRXU	0.9249	1.0000	20000	0	Healthcare
04/12/2012	Oaktree Capital Group	OAK	0.8147	1.0000	260000	0	Financials
08/03/2010	Trius Therapeutics	TSRX	0.8031	1.0000	60000	0	Healthcare
11/08/2007	ICx Technologies	ICXT	1.0000	1.0000	1420000	85000	High Technology
08/19/2004	Google	GOOG	0.6803	1.0000	180000	0	High Technology
07/20/1999	Genentech	DNA	0.6134	1.0000	1040000	5000	Healthcare
05/10/2013	BioAmber	BIOA	0.9561	0.9828	80000	0	Materials
07/24/2014	Pfenex	PFNX	0.9092	0.9807	180000	0	Healthcare
10/28/2009	Addus HomeCare	ADUS	0.9460	0.9715	40000	0	Healthcare
05/18/2012	Facebook	FB	0.7983	0.9694	1350000	270000	High Technology
02/03/2004	TRW Automotive Holdings	TRW	0.8298	0.9647	0	675000	Industrials
04/10/2014	Ally Financial	ALLY	0.8373	0.9552	2110000	0	Financials
05/05/2005	Lazard	LAZ	0.8366	0.9545	290000	0	Financials
05/24/2006	Vonage Holdings	VG	0.9194	0.9536	805000	150000	Telecommunications
07/30/1999	Biopure	BPUR	0.9402	0.9526	20000	0	Healthcare
06/12/2001	Kraft Foods	KFT	0.8031	0.9512	0	59500	Consumer Staples
06/19/2001	The Princeton Review	REVU	0.9299	0.9470	60000	0	Consumer Products and Services
10/08/2009	Omeros	OMER	0.9200	0.9427	60000	0	Healthcare
04/10/2014	Adamas Pharmaceuticals	ADMS	0.9172	0.9379	10000	0	Healthcare
05/09/2013	Quintiles Transnational	Q	0.7629	0.9358	40000	0	Consumer Products and Services
02/10/2012	Homestreet	HMST	0.7362	0.9349	5000	2350	Financials
03/08/2007	Clearwire	CLWR	0.8155	0.9343	80000	0	High Technology
04/23/2008	American Water Works	AWK	0.8382	0.9314	300000	100000	Energy and Power
03/22/2013	West Corp	WSTC	0.8517	0.9305	40000	0	Consumer Products and Services
11/18/2010	General Motors	GM	0.7752	0.9294	9570000	284500	Industrials
11/17/2011	Delphi Automotive	DLPH	0.8284	0.9263	396429	40500	Industrials
05/03/1999	CONSOL Energy	CNX	0.9018	0.9259	550000	226250	Materials
03/09/2011	HCA Holdings	HCA	0.7767	0.9200	200000	268250	Healthcare
02/11/2011	Kinder Morgan	KMI	0.7760	0.9193	190000	0	Energy and Power
12/13/2013	Cheniere Energy Partners	CQH	0.8357	0.9165	2630000	201800	Energy and Power
	mean		*0.8426*	*0.9556*	*732,880.9667*	*78,938.3333*	
	std		*0.0860*	*0.0284*	*1,793,480.2481*	*147,547.0496*	
	min		*0.6134*	*0.9165*	*0.0000*	*0.0000*	
	max		*1.0000*	*1.0000*	*9,570,000.0000*	*675,000.0000*	
07/18/2014	SAGE Therapeutics	SAGE	0.4803	0.5666	70000	0	Healthcare
06/22/1999	Ramp Networks	RAMP	0.5274	0.5622	20000	0	High Technology
03/09/2005	International Sec Exchange	ISE	0.4755	0.5618	0	6000	Financials

06/17/1998	software.net	SWNT	0.5455	0.5499	20000	0	High Technology
07/24/2013	Agios Pharmaceuticals	AGIO	0.4622	0.5480	40000	0	Healthcare
12/13/2012	SolarCity	SCTY	0.5450	0.5475	230000	2000	Industrials
12/19/2007	Orion Energy Systems	OESX	0.4877	0.5457	100000	0	Industrials
07/20/2011	Zillow	Z	0.4490	0.5413	40000	0	High Technology
05/29/2014	Resonant	RESN	0.5295	0.5409	40000	0	High Technology
09/20/2013	FireEye	FEYE	0.4462	0.5382	120000	0	High Technology
03/23/1998	ISS Group	ISSX	0.4376	0.5345	80000	0	High Technology
01/30/1998	VeriSign	VRSN	0.4409	0.5079	60000	0	High Technology
12/10/1999	Freemarkets	FMKT	0.1377	0.4948	80000	0	Consumer Products and Services
09/25/2013	Foundation Medicine	FMI	0.4089	0.4923	80000	0	Healthcare
09/20/2007	athenahealth	ATHN	0.4072	0.4904	40000	0	High Technology
07/27/2000	Corvis	CORV	0.3413	0.4886	40000	0	Telecommunications
02/25/2000	Intersil Holding	ISIL	0.3718	0.4862	80000	0	High Technology
07/22/1999	MP3.COM	MPPP	0.3552	0.4814	40000	0	High Technology
08/18/2000	WJ Communications	WJCI	0.3984	0.4743	0	1500	High Technology
12/12/2013	Kindred Biosciences	KIN	0.4704	0.4723	1940000	0	Healthcare
02/25/2000	DigitalThink	DTHK	0.3877	0.4551	40000	0	Consumer Products and Services
11/19/2014	Second Sight Med Prod	EYES	0.3619	0.3999	10000	0	Healthcare
07/28/1999	drugstore.com	DSCM	0.2877	0.3696	140000	0	Retail
07/20/1999	Engage Technologies	ENGA	0.2938	0.3595	20000	0	High Technology
12/03/1998	Ticketmaster Online-CitySearch	TMCS	0.2793	0.3411	36000	0	High Technology
04/07/1999	Rhythms NetConnections	RTHM	0.2440	0.3366	20000	0	Telecommunications
07/17/1998	Broadcast.Com	BCST	0.2304	0.3117	20000	0	High Technology
12/01/1999	McAfee.com	MCAF	0.2190	0.2717	20000	0	High Technology
03/29/1999	priceline.com	PCLN	0.1862	0.2569	80000	0	High Technology
02/10/1999	Healtheon	HLTH	0.2047	0.2429	30000	0	Healthcare
	mean		*0.3804*	*0.4590*	*117,866.6667*	*316.6667*	
	std		*0.1152*	*0.1005*	*347,410.0959*	*1,163.2545*	
	min		*0.1377*	*0.2429*	*0.0000*	*0.0000*	
	max		*0.5455*	*0.5666*	*1,940,000.0000*	*6,000.0000*	

Similarly, Table 3 presents the top and lowest 30 IPOs from the reduced sample (excluding overpriced IPOs, N=317). Under the VRS assumption, all IPOs lie on the VRS frontier and exhibit an efficiency score of 1. Under CRS, only 3 IPOs are deemed inefficient with the majority of the top performers lying on the CRS frontier. This group comprises 9 sectors (Consumer Staples, Energy and Power, Financials, Healthcare, High Technology, Industrials, Materials, Media and Entertainment and Telecommunications) which appear almost identical to those featured in the full sample. Under the CRS (VRS) assumption, the lowest 30 IPOs have a mean efficiency score of 0.4653 (0.4877). The majority of these issuers come from the 'High Technology' sector,

corroborating our previous findings[13]. Again, we observe that among the top performers 10 out of 30 companies have donated PAC money. The respective proportion for the lowest group is only 4 out of 30. This provides further evidence that IPOs with limited underpricing tend to rely on PAC campaigns. However, it should be emphasized that the top performers in the reduced sample include fewer companies which combine lobbying and PAC compared to the full sample. This, in turn, suggests that it is mainly the overpriced IPOs that employ both contribution types.

Table 3
Efficiency analysis- 317 IPOs: top and worst performers

We present the top and worst 30 IPOs for the reduced sample (317 underpriced IPOs) in terms of their ability to minimize underpricing. We sort the IPOs based on their efficiency performance under the VRS assumption in order to account for differences between sectors. When an IPO is efficient (i.e. efficiency score equal to 1.000) under the CRS assumption, it is also efficient under the VRS assumption. Additionally, we identify the IPO firm's sector alongside with the lobby and PAC donation amounts. The main descriptive statistics of the efficiency estimates, lobby and PAC amounts are tabulated below each IPO group.

Listing Date	Company	Ticker	CRS	VRS	Lobby Money	PAC Money	Sector
07/31/2014	Marinus Pharmaceuticals	MRNS	1.0000	1.0000	40000	0	Healthcare
12/12/2013	Kindred Biosciences	KIN	1.0000	1.0000	1940000	0	Healthcare
03/20/2013	Tetraphase Pharmaceuticals	TTPH	1.0000	1.0000	60000	0	Healthcare
05/18/2012	Facebook	FB	0.9940	1.0000	1350000	270000	High Technology
06/24/2011	KiOR	KIOR	1.0000	1.0000	120000	0	Energy and Power
12/17/2010	Fortegra Financial	FRF	1.0000	1.0000	150000	0	Financials
11/19/2010	Aeroflex Holding	ARX	1.0000	1.0000	8700	0	High Technology
08/03/2010	Trius Therapeutics	TSRX	1.0000	1.0000	60000	0	Healthcare
04/22/2010	Codexis	CDXS	1.0000	1.0000	190000	0	Materials
11/16/2007	Internet Brands	INET	1.0000	1.0000	80000	0	High Technology
02/09/2007	VeriChip	CHIP	1.0000	1.0000	120000	0	Telecommunications
12/14/2006	NewStar Financial	NEWS	1.0000	1.0000	0	15000	Financials
11/02/2005	Cbeyond Communications	CBEY	1.0000	1.0000	100000	0	Telecommunications
08/17/2005	Rockwood Holdings	ROC	1.0000	1.0000	140000	0	Materials
06/14/2005	Premium Standard Farms	PORK	1.0000	1.0000	40000	18075	Consumer Staples
02/10/2005	Nasdaq Stock Market	NDAQ	1.0000	1.0000	0	51400	Financials
01/21/2005	ViaCell	VIAC	1.0000	1.0000	20000	0	Healthcare
08/19/2004	Google	GOOG	0.8471	1.0000	180000	0	High Technology
08/05/2004	RightNow Technologies	RNOW	1.0000	1.0000	110000	0	High Technology
07/30/2004	EnerSys	ENS	1.0000	1.0000	0	150000	High Technology
05/24/2004	Genworth Financial	GNW	1.0000	1.0000	180000	0	Financials
08/02/2001	Bunge	BG	1.0000	1.0000	120000	0	Consumer Staples
06/12/2001	Kraft Foods	KFT	1.0000	1.0000	0	59500	Consumer Staples

[13] The majority of high performers within the reduced sample come from companies operating in the "High Technology" sector. This contradicts our previous findings. However, we identify the cause in the exclusion of overpriced IPOs.

03/15/2001	SureBeam Corp(Titan Corp)	SURE	1.0000	1.0000	220000	500	Industrials
07/29/1999	Lennox International	LII	1.0000	1.0000	0	8000	Industrials
07/28/1999	American Nat. Can Group	CAN	1.0000	1.0000	0	7300	Materials
07/20/1999	Engage Technologies	ENGA	0.7638	1.0000	20000	0	High Technology
07/22/1998	USEC	USU	1.0000	1.0000	60000	0	Materials
05/27/1998	Capstar Broadcasting	CRB	1.0000	1.0000	60000	0	Media and Entertainment
05/11/1998	MGC Communications	MGCX	1.0000	1.0000	0	5500	Telecommunications
	mean		*0.9868*	*1.0000*	*178,956.6667*	*19,509.1667*	
	std		*0.0505*	*0.0000*	*411,343.9300*	*55,975.2033*	
	min		*0.7638*	*1.0000*	*0.0000*	*0.0000*	
	max		*1.0000*	*1.0000*	*1,940,000.0000*	*270,000.0000*	
02/08/2007	Accuray	ARAY	0.6322	0.6322	200000	0	Healthcare
10/06/1999	PlanetRx.com	PLRX	0.6154	0.6154	30000	0	Retail
12/19/2007	Orion Energy Systems	OESX	0.6072	0.6072	100000	0	Industrials
11/07/2013	Twitter	TWTR	0.5791	0.6040	90000	0	High Technology
05/17/1999	Nextcard	NXCD	0.5970	0.5984	20000	0	Financials
07/18/2014	SAGE Therapeutics	SAGE	0.5980	0.5980	70000	0	Healthcare
03/09/2005	International Sec Exchange	ISE	0.5921	0.5921	0	6000	Financials
12/12/2013	ARAMARK Holdings	ARMK	0.5858	0.5858	200000	2000	Retail
07/24/2013	Agios Pharmaceuticals	AGIO	0.5754	0.5756	40000	0	Healthcare
07/20/2011	Zillow	Z	0.5591	0.5615	40000	0	High Technology
09/20/2013	FireEye	FEYE	0.5556	0.5580	120000	0	High Technology
03/23/1998	ISS Group	ISSX	0.5448	0.5552	80000	0	High Technology
01/30/1998	VeriSign	VRSN	0.5490	0.5490	60000	0	High Technology
09/25/2013	Foundation Medicine	FMI	0.5092	0.5112	80000	0	Healthcare
09/20/2007	athenahealth	ATHN	0.5070	0.5091	40000	0	High Technology
02/25/2000	Intersil Holding	ISIL	0.4630	0.5007	80000	0	High Technology
08/18/2000	WJ Communications	WJCI	0.4961	0.4967	0	1500	High Technology
12/10/1999	Freemarkets	FMKT	0.1714	0.4948	80000	0	Consumer Products and Services
07/27/2000	Corvis	CORV	0.4249	0.4919	40000	0	Telecommunications
07/22/1999	MP3.COM	MPPP	0.4423	0.4914	40000	0	High Technology
02/25/2000	DigitalThink	DTHK	0.4828	0.4828	40000	0	Consumer Products and Services
11/19/2014	Second Sight Med Prod	EYES	0.4507	0.4507	10000	0	Healthcare
07/28/1999	drugstore.com	DSCM	0.3582	0.3822	140000	0	Retail
07/20/1999	Genentech	DNA	0.3659	0.3741	1040000	5000	Healthcare
12/03/1998	Ticketmaster Online	TMCS	0.3478	0.3542	36000	0	High Technology
04/07/1999	Rhythms NetConnections	RTHM	0.3038	0.3421	20000	0	Telecommunications
07/17/1998	Broadcast.Com	BCST	0.2869	0.3183	20000	0	High Technology
12/01/1999	McAfee.com	MCAF	0.2727	0.2832	20000	0	High Technology
03/29/1999	priceline.com	PCLN	0.2319	0.2611	80000	0	High Technology
02/10/1999	Healtheon	HLTH	0.2549	0.2550	30000	0	Healthcare
	mean		*0.4653*	*0.4877*	*94,866.6667*	*483.3333*	
	std		*0.1331*	*0.1142*	*185,565.8138*	*1,441.2838*	
	min		*0.1714*	*0.2550*	*0.0000*	*0.0000*	
	max		*0.6322*	*0.6322*	*1,040,000.0000*	*6,000.0000*	

Conceivably, setting off to analyze the differential effect of lobbying and PAC on IPO performance is a meaningful endeavour only to the extent that the above efficiency scores would differ in the absence of either type of expenditure. To elucidate the association with the issuer's ability to minimize underpricing, we conduct the bootstrap-based nonparametric test proposed by Li et al. (2009) and report the results in Table 4[14]. The upper part of the table engages the full sample for the CRS and VRS assumptions. With $f(\cdot)$ and $g(\cdot)$ denoting the density functions of unconditional and conditional efficiency estimates, respectively, contributions are shown to produce an effect that fulfils all conventional levels of significance. The lower part extends this analysis to the reduced sample and corroborates further the relationship. Evidently, lobby and PAC money alter issuers' ability to evaluate IPOs and this reflects upon the estimated efficiency levels. Given the strength of the association, we can now turn to disentangling the effect by donation type and investigate the optimal appropriation of an issuer's political budget.

Table 4
Kernel consistent density equality tests

We implement a consistent integrated squared differences test for the equality of densities of conditional and unconditional efficiencies under the CRS and VRS assumptions in the full and reduced IPO samples. Following Simar and Zelenyuk (2006), we trim the DEA-estimates from values equal to unity and conduct the Li et al. (2009) test applying the least-squares cross validation criterion and bootstrap methods for the null distribution of the statistic (1,000 replications have been applied).

Full sample (including overpriced IPOs)		
	Test Statistic	*p-value*
$H_0 : f(CRS) = g(CRS \mid M)$		
$H_1 : f(CRS) \neq g(CRS \mid M)$	286.2809	0.0000
$H_0 : f(VRS) = g(VRS \mid M)$		
$H_1 : f(VRS) \neq g(VRS \mid M)$	175.7127	0.0000

[14] Following Simar and Zelenyuk (2006), we trim the estimates that are equal to unity (Algorithm I) and perform the bootstrap Li et al. (2009) test. Hence, our results are unaffected by sampling variation or noise from the DEA estimation.

Reduced sample (excluding overpriced IPOs)		
	Test Statistic	*p-value*
$H_0 : f\left(CRS\right) = g\left(CRS\middle\vert M\right)$		
$H_1 : f\left(CRS\right) \neq g\left(CRS\middle\vert M\right)$	226.1246	0.0000
$H_0 : f\left(VRS\right) = g\left(VRS\middle\vert M\right)$		
$H_1 : f\left(VRS\right) \neq g\left(VRS\middle\vert M\right)$	131.1409	0.0000

Figure 4 illustrates graphically the effect of lobby and PAC contributions on IPO efficiency levels as surfaces in a three-dimensional space (c.f. Bădin et al. (2012)). Drawing evidence from the full sample (N=379 IPOs), subfigures "a", "c", "e" and "g" present the results from the nonparametric regression analysis under the CRS assumption; subfigures "b", "d", "f" and "h" portray the respective findings under VRS[15]. Subfigure "a" reveals a nonlinear relationship between lobbying and IPO performance, resembling an inverted "U"-shape. For lower levels of lobbying money, the effect on efficiency is positive up to a certain threshold value. Beyond that point a negative association arises, indicated by a downwards slopping nonparametric regression line. An inverted "U"-shape relationship[16] is also evident in VRS (subfigure "b"). In the case of PAC, we observe an increasing nonlinear nonparametric regression line (subfigure "a"), showing a positive influence on IPO efficiency levels. Under VRS, the effect is more pronounced, indicated by a steeper increasing nonparametric regression line. Modifying further our sampling to account for an issuer's particular economic sector, new interesting patterns emerge.

[15] Subfigures "a" and "b" present the effect of lobby and PAC money for all IPOs of the full sample. The rest subfigures illustrate the effect based on sub-sampling analysis for three sectors (Financials, Energy and Power and Industrials). The choice is based on the fact that the highest levels of donations for lobby and PAC money come from companies operating in these sectors (see also Figure 1).

[16] Since the CRS measurement has a higher discriminative power than VRS, the examined effects in some cases may be more emphatic under the CRS assumption.

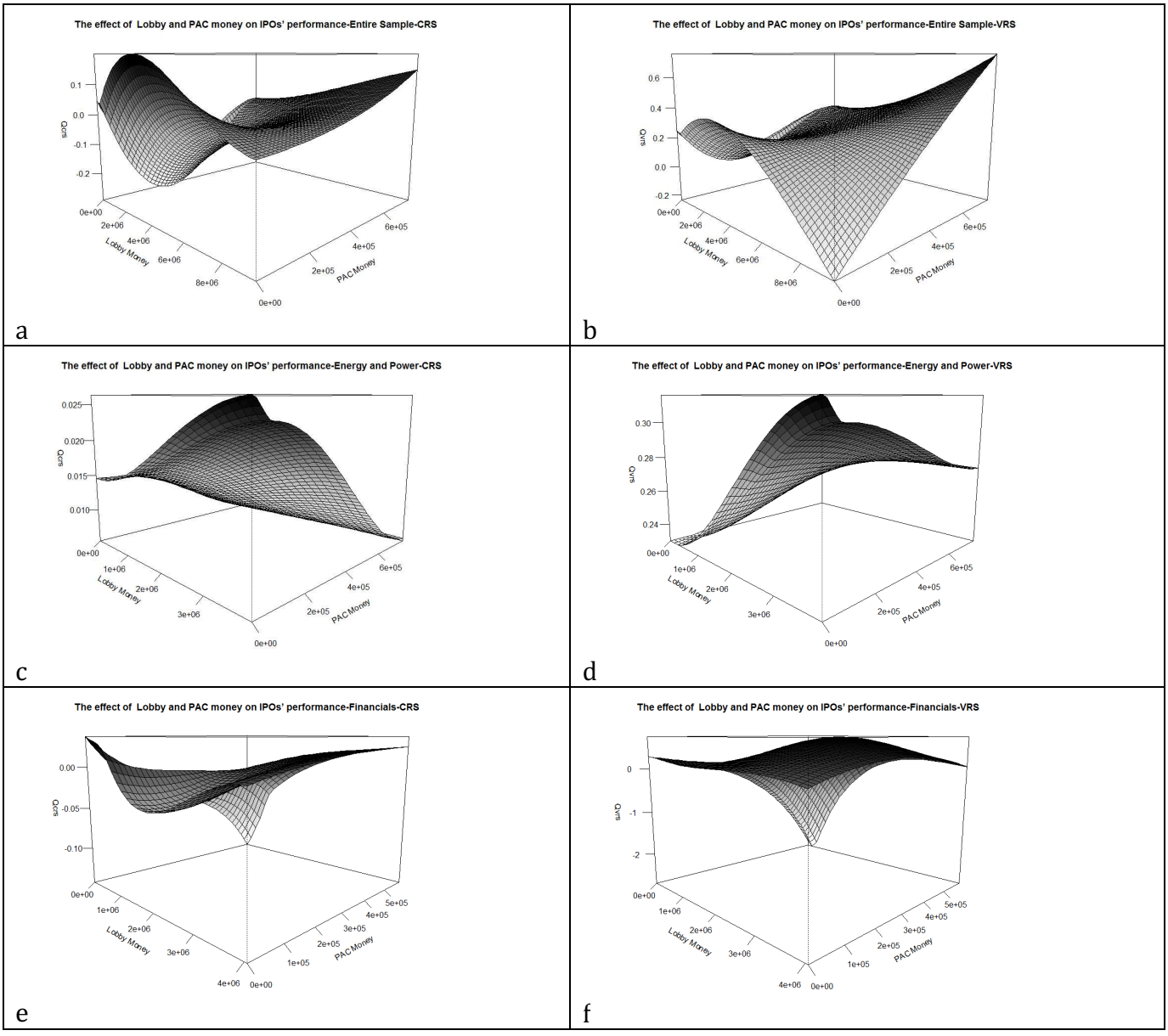
Indeed, focusing on IPOs from the "Energy and Power" sector, we observe that the effects are not uniform. Under both CRS (subfigure "c") and VRS (subfigure "d"), PAC donations have a nonlinear negative effect on efficiency levels. However, lobby money appears to exert a highly positive influence. In both cases, the nonlinearities suggest that companies operating in this sector are better off with lobbying rather than PAC expenditure. In the Financial sector, under the CRS assumption (subfigure "e") lobbying has a "U"-shape association with efficiency level, whereas PAC accounts for a positive effect, indicated by a nonlinear increasing nonparametric regression line. However, when we assume VRS (subfigure "f"), the effect of lobbying turns to neutral, while the effect of PAC exhibits a light form of an inverted "U"-shape relationship. Therefore, the influence of the exogenous factors is also attributable to scale effects[17]. Accordingly, lobby and PAC contributions may have different implications for larger companies in the sector compared to smaller ones. Finally, the Industrial sector, under both CRS (subfigure "g") and VRS (subfigure "h") reveals a positive effect for PAC contributions.[18] However, lobbying gives rise to heterogeneous patterns. Specifically, the CRS assumption yields a negative effect, whereas under VRS there is a "U"-shape relationship, suggesting that when we account for offer price levels the effect can vary.

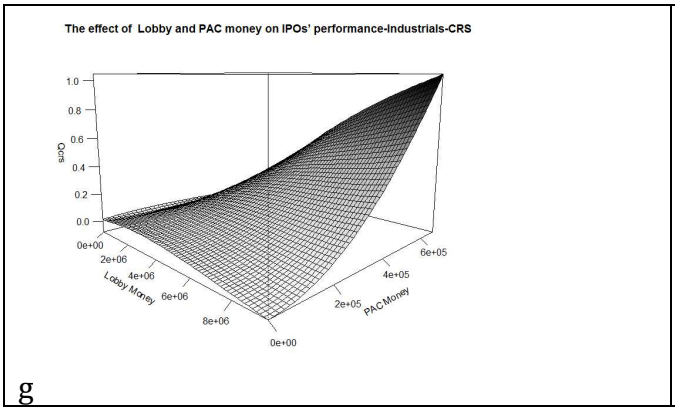
[17] In our case, the different size is attributed to differences in IPO offer price.

[18] This positive effect is more pronounced under CRS.

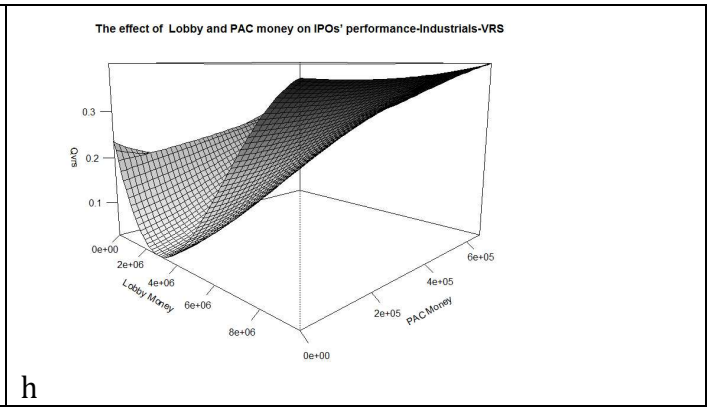
Figure 4
The effect of lobby and PAC money on IPO performance (full sample-379 IPOs): Nonparametric regression

The three-dimensional graphs represent the results of local constant estimators indicating the effect of PAC and lobby money on IPO performance (efficiency). These regressions apply for bandwidth selection the least-squares cross validation criterion. The vertical axes indicate the ratio of conditional to unconditional measures, whereas the horizontal axes represent the amounts of lobby and PAC money donated by IPO firms. Subfigures 4a, 4c, 4e and 4g illustrate the effect of lobby and PAC money under the CRS assumption, and subfigures 4b, 4d, 4f and 4h show the effect under the VRS assumption.





g



h

In a similar approach, Figure 5 describes the effect of lobby and PAC on IPO efficiency based on the reduced sample (N=317). Subfigures “a” and “b” present the overall results. Under CRS, lobbying produces a “U”-shape relationship, whereas under VRS the association becomes negative. This suggests that scale effects can drastically alter the impact on issuers’ efficiency. Conversely, the overall PAC effect remains positive under both assumptions, indicated by an increasing nonlinear regression line. This is consistent with the full sample results which are proven robust to the inclusion/exclusion of overpriced IPOs.

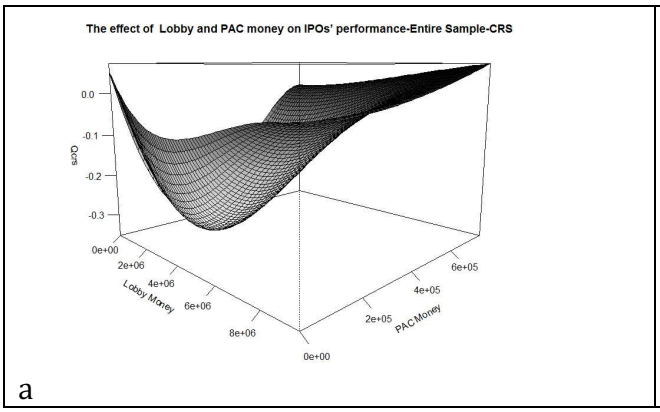
Drawing separate evidence from the Energy and Power sector, we observe that political expenditure exerts a similar influence under both CRS (subfigure “c”) and VRS (subfigure “d”). In particular, lobby money has a nonlinear positive effect on IPO efficiency levels, whereas PAC has a nonlinear negative effect. The Financial sector (subfigure “f”) demonstrates that under VRS the effects of both lobby and PAC money are almost identical with those previously examined for the full sample. However, under CRS (subfigure “e”) lobbying gives rise to an inverted “U”-shape, whereas previously it formed a “U”-shape. In this case, the lobbying influence remains conditional on sampling and implies that the CRS assumption in some industries may be unrealistic. Finally, subfigure “g” engages firms operating in the Industrial sector. In overall terms, the results are robust since they agree with our earlier evidence, suggesting a negative association with lobbying and a positive one with PAC money. In addition, under the assumption of VRS (subfigure “h”) the effect

of PAC money is positive as it has also been for the full sample; however, lobbying leads to a "U"-shape relationship, suggesting a negative effect for lower levels of lobbying contributions and a positive effect for higher levels. This contradicts our previous findings which portrayed a monotonically negative effect for lobbying. Once again, the assumption of VRS does not produce robust results.

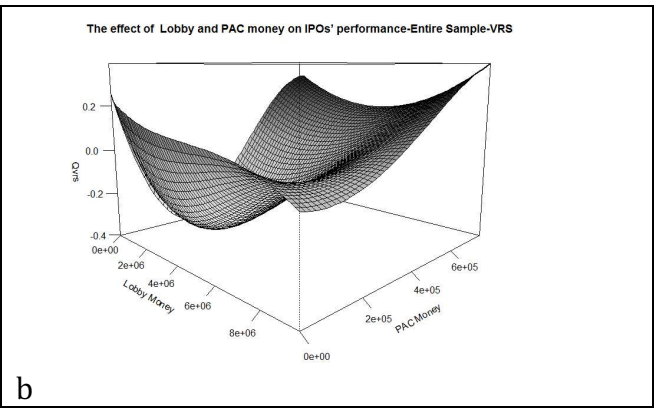
Conclusively, the evidence from both samples converges on the positive influence of PAC; the dollar intensity of these campaigns tends to constrain underpricing. Given that IPO firms channel significantly larger amounts towards lobbying than PAC, our findings suggest that the effects of such donations are not deterministic to IPO performance and depend heavily on the particular sectors that the companies operate in. Likewise, scale effects can determine the effect of lobby and PAC money on IPO efficiency levels. Invariably, the relationships are highly nonlinear, justifying our fully nonparametric treatment.

Figure 5
The effect of lobby and PAC money on IPO performance (reduced sample-317 IPOs): Nonparametric regression

The three-dimensional graphs represent the results of local constant estimators indicating the effect of PAC and lobby money on IPO performance (efficiency). These regressions apply for bandwidth selection the least-squares cross validation criterion. The vertical axes indicate the ratio of conditional to unconditional measures, whereas the horizontal axes represent the amounts of lobby and PAC money donated by IPO firms. Subfigures 4a, 4c, 4e and 4g illustrate the effect of lobby and PAC money under the CRS assumption, and subfigures 4b, 4d, 4f and 4h show the effect under the VRS assumption.



a



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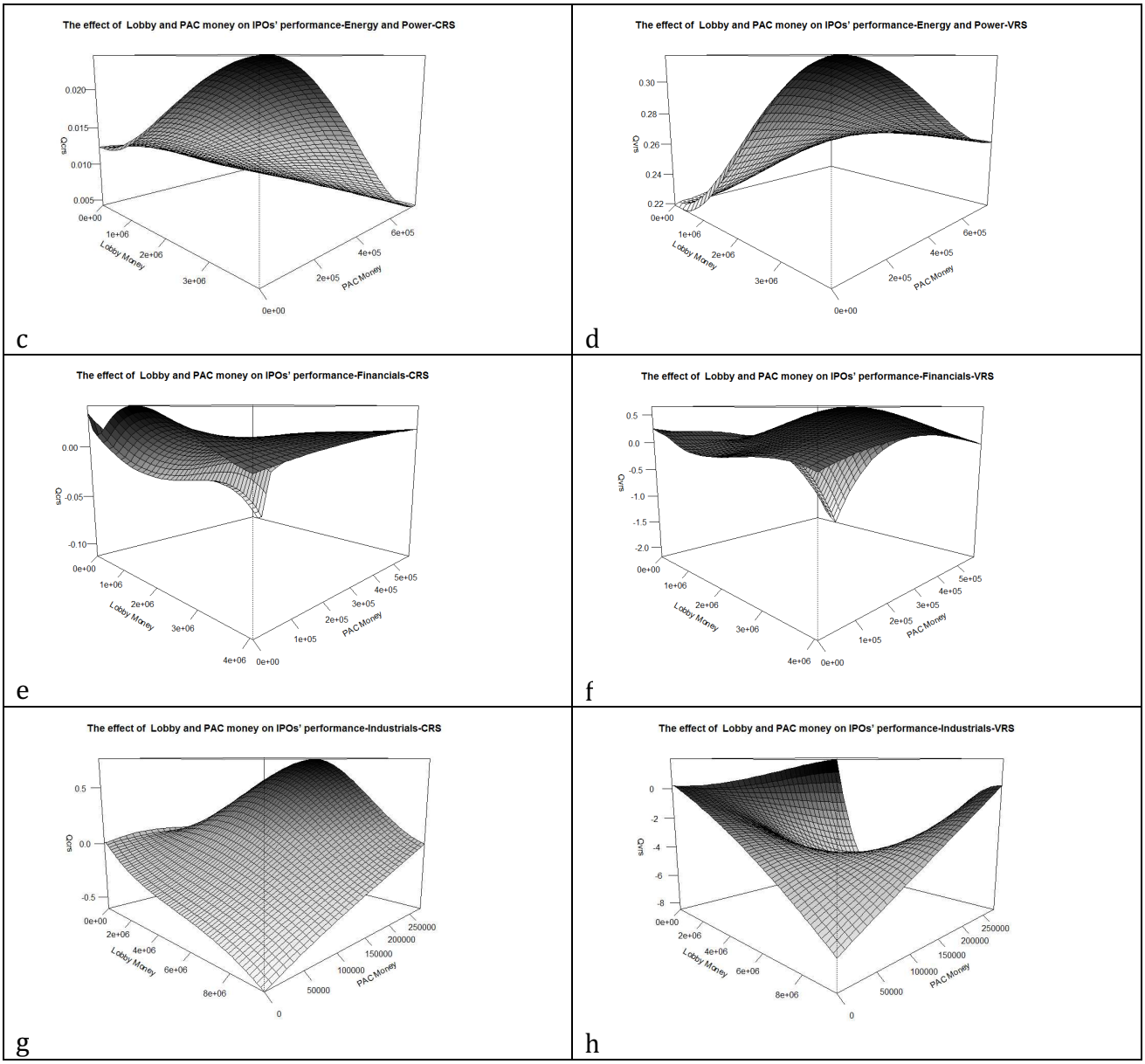

V. Discussion

Overall, our results show that IPOs with reduced underpricing tend to come from companies which have employed PAC campaigns and that companies with overpriced IPOs are mainly those that donate both lobby and PAC money. There is a nonlinear relationship between lobby money and IPO performance (the inverted "U"-shape).

PAC contributions produce a robustly positive effect across both full and reduced samples; the inclusion/exclusion of overpriced IPOs does not alter the effect of PAC money. This is apparent in the IPOs of Industrial firms (where, in contrast, the influence of lobbying assumes a variety of

patterns). Non-coincidentally, this sector includes industries known for their high political expenditure such as transport equipment and defense system manufacturers, for which historically the U.S. government is the single most influential buyer.[19]

Lobbying, as a message-oriented activity, lends itself to circumstances where the elements of communication and timely interactions with legislators are crucial. The Energy and Power sector, which is extensively regulated, illustrates this notion by a decisive advantage for lobbying IPOs. Commonly under public scrutiny for safety and environmental concerns, these firms must produce compelling arguments about the way that their operations affect other stakeholders - especially if, as noted by Milyo (2001), an incumbent's objective function revolves around the issues of re-election, career progression within Congress and ideology promotion. Where discontent is caused among a candidate's constituents, a firm not only depletes its political capital but may also trigger enactment of constraining legislation.

For the Financial sector, however, the analysis reveals patterns which lack robustness as well as a definite direction. This is intriguing, given the large amounts that many of these firms spend[20], the complex institutional framework and the massive assistance which the federal government has provided during periods of turbulence. The idiosyncrasy of financial organizations may account for the blurred effect. Notwithstanding the high degree of regulation and frequent government intervention, operators in this sector are not as dependent on political favoritism for the success of their businesses as is the case, for example, with regulated industries from the Industrial sector. Financial institutions are essential to economic activity and exert de facto political influence.

[19] IBISWorld reports that in 2013, the top contributing defence and aerospace firms had 56.1% of turnover coming from federal contracts, while in some cases the figure is around 90%.

[20] Approximately 16.5% of total political expenditure over the last five years, though because this sector mainly comprises large businesses, political expenditure is not a large proportion of each company's expenditure.

VI. Additional robustness tests

The DEA estimators (described by equations 12 and 13) measure IPO efficiency relative to an estimate of an unobserved true frontier. Consequently, remaining conditional on the sample from an underlying data-generating process (DGP), these estimators are biased by construction. In our setting, the magnitude of the bias can be computed as:

$$BIAS\left(\hat{\phi}_{CRS}\left(e_0,b_0\right)\right)=E\left(\hat{\phi}_{CRS}\left(e_0,b_0\right)\right)-\phi_{CRS}\left(e_0,b_0\right), \tag{19}$$

$$BIAS\left(\hat{\phi}_{VRS}\left(e_0,b_0\right)\right)=E\left(\hat{\phi}_{VRS}\left(e_0,b_0\right)\right)-\phi_{VRS}\left(e_0,b_0\right). \tag{20}$$

Then, the bootstrap bias estimate of the original estimators under the CRS and VRS assumptions corresponds to the empirical analog of equations (14) and (15):

$$\hat{BIAS}_B\left(\hat{\phi}_{CRS}\left(e_0,b_0\right)\right)=B^{-1}\sum_{b=1}^{B=2000}\hat{\phi}^*_{CRS,b}\left(e_0,b_0\right)-\hat{\phi}_{CRS}\left(e_0,b_0\right), \tag{21}$$

$$\hat{BIAS}_B\left(\hat{\phi}_{VRS}\left(e_0,b_0\right)\right)=B^{-1}\sum_{b=1}^{B=2000}\hat{\phi}^*_{VRS,b}\left(e_0,b_0\right)-\hat{\phi}_{VRS}\left(e_0,b_0\right). \tag{22}$$

Simar and Wilson (1998, 2000a,b) have proposed bootstrap methods for inference and bias correction of the original DEA estimates in order to improve accuracy. Accordingly, the bias-corrected estimators under the CRS and VRS assumptions can be calculated as:

$$\begin{aligned}\hat{\hat{\phi}}_{CRS}\left(e_0,b_0\right)&=\hat{\phi}_{CRS}\left(e_0,b_0\right)-\hat{BIAS}_B\left(\hat{\phi}_{CRS}\left(e_0,b_0\right)\right)\\&=2\hat{\phi}_{CRS}\left(e_0,b_0\right)-B^{-1}\sum_{b=1}^{B=2000}\hat{\phi}^*_{CRS,b}\left(e_0,b_0\right),\end{aligned} \tag{23}$$

$$\begin{aligned}\hat{\hat{\phi}}_{VRS}\left(e_0,b_0\right)&=\hat{\phi}_{VRS}\left(e_0,b_0\right)-\hat{BIAS}_B\left(\hat{\phi}_{VRS}\left(e_0,b_0\right)\right)\\&=2\hat{\phi}_{VRS}\left(e_0,b_0\right)-B^{-1}\sum_{b=1}^{B=2000}\hat{\phi}^*_{VRS,b}\left(e_0,b_0\right).\end{aligned} \tag{24}$$

The sample variance of the bootstrap values $\hat{\phi}^*_{CRS,b}\left(e_0,b_0\right)$, $\hat{\phi}^*_{VRS,b}\left(e_0,b_0\right)$ provides us with an estimate $\hat{\sigma}^2$ of the variance of $\hat{\phi}_{CRS}\left(e_0,b_0\right)$ and $\hat{\phi}_{VRS}\left(e_0,b_0\right)$:

(25) $$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B=2000}\left[\hat{\phi}^*_{CRS,b}\left(e_0,b_0\right) - B^{-1}\sum_{b=1}^{B=2000}\hat{\phi}^*_{CRS,b}\left(e_0,b_0\right)\right]^2,$$

(26) $$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B=2000}\left[\hat{\phi}^*_{VRS,b}\left(e_0,b_0\right) - B^{-1}\sum_{b=1}^{B=2000}\hat{\phi}^*_{VRS,b}\left(e_0,b_0\right)\right]^2.$$

Finally, we can construct the confidence intervals of the two estimators using the empirical bootstrap distribution of the pseudo estimates $\hat{\phi}^*_{CRS,b}, \hat{\phi}^*_{VRS,b}, b = 1,...,2000$ in order to find the interval values of $\hat{\alpha}_\alpha$ and $\hat{b}_\alpha$. Then, the $\left(1-\alpha\right)$ percent confidence interval can be expressed as:

(27) $$\hat{\phi}_{CRS}\left(e_0,b_0\right) + \hat{\alpha}_\alpha \le \phi_{CRS}\left(e_0,b_0\right) \le \hat{\phi}_{CRS}\left(e_0,b_0\right) + \hat{b}_\alpha,$$

(28) $$\hat{\phi}_{VRS}\left(e_0,b_0\right) + \hat{\alpha}_\alpha \le \phi_{VRS}\left(e_0,b_0\right) \le \hat{\phi}_{VRS}\left(e_0,b_0\right) + \hat{b}_\alpha.$$

As per Simar and Wilson (1998, 2000b), we apply bootstrap-based inference algorithms for computing the bias-corrected efficiency estimates alongside with the 95% bootstrap confidence intervals. This allows us to capture any variations in the baseline results once the sample bias has been eliminated (Simar and Wilson (2000a)). Tables 5 and 6 report the new estimates under CRS and VRS, respectively, for the top and lowest 30 IPOs in the full sample (N=379), whereas Tables 7 and 8 extend this analysis to the reduced sample (excluding overpriced IPOs, N= 317)[21]. In an important divergence from the figures presented in Tables 2 and 3, efficiency may not take the value of 1. Rather, the IPO performance is determined based on the bias-corrected efficiency score; the higher the estimate, the greater the performance.

[21] For our analysis we have applied 2,000 replications as suggested by Simar and Wilson (1998, 2000b). Due to their large volume, these results are not tabulated. However, they are available upon request. Finally, for our bootstrap calculations, we acknowledge the use of the 'FEAR' – package which is integrated in the R-programming language (Wilson (2008)).

More closely, within the full sample and under the CRS assumption (Table 5), the highest performers comprise IPOs from 8 different sectors (Consumer Products and Services, Energy and Power, Financials, Healthcare, High Technology, Industrials, Materials and Telecommunications). The lowest performing group also involves 8 sectors (Consumer Products and Services, Financials, Healthcare, High Technology, Industrials, Media and Entertainment, Retail and Telecommunications) with 'High Technology' accounting for the majority of the IPOs. On average, the top (lowest) 30 performers have a bias-corrected efficiency score of 0.8758 (0.3682). In a similar spirit to our previous analysis, 6 out of the 30 top performing companies have donated PAC money; the respective proportion for the lowest performers is only 2 out of 30.

Under the VRS assumption (Table 6), the highest performing group includes IPOs from 10 sectors (Financials, Energy and Power, Consumer Staples, Consumer Products and Services, Telecommunications, Real Estate, Materials, Industrials, High Technology and Healthcare). Appearing less diverse, the lowest performing group comprises 7 sectors (Consumer Products and Services, Telecommunications, Retail, Industrials, High Technology, Healthcare and Financials). The top (lowest) 30 performers have a mean value of bias-corrected efficiency score of 0.9216 (0.4389). Importantly, 11 of the top IPOs have been active in both lobbying and PAC. This comes in striking contrast to the bottom group whereby 1 company employs both contribution types out of a total of 3 PAC donors. Finally, the VRS regime confirms that the lowest efficiency levels come from companies in the High Technology sector.

Table 5
Bootstrap efficiency analysis- 379 IPOs: top and worst performers (CRS assumption)

We present the top and worst 30 IPOs for the full sample (N=379) in terms of their ability to minimize underpricing. We sort the IPOs based on their bootstrap efficiency performance under the CRS assumption. High bootstrap efficiency levels indicate high IPO performance. Additionally, we identify the IPO firm's sector alongside with the lobby and PAC donation amounts. Also we present the 95% bootstrap confidence intervals of the estimations alongside with the estimated bias and its standard deviation. Finally, the main descriptive statistics are tabulated below each IPO group.

Listing Date	Company	Ticker	Bias Corrected CRS	Estimated Bias	STD of the estimated Bias	Lower Bound	Upper Bound	Lobby Money	PAC Money	Sector
11/08/2007	ICx Technologies	ICXT	0.9861	0.0139	0.0002	0.9583	0.9997	1420000	85000	High Technology
05/10/2013	BioAmber	BIOA	0.9428	0.0133	0.0001	0.9162	0.9558	80000	0	Materials
10/28/2009	Addus HomeCare	ADUS	0.9327	0.0132	0.0001	0.9064	0.9455	40000	0	Healthcare
07/30/1999	Biopure	BPUR	0.9271	0.0131	0.0001	0.9009	0.9399	20000	0	Healthcare
06/19/2001	The Princeton Review	REVU	0.9170	0.0129	0.0001	0.8911	0.9296	60000	0	Consumer Products and Services
07/29/2014	ContraFect	CFRXU	0.9121	0.0128	0.0001	0.8863	0.9246	20000	0	Healthcare
10/08/2009	Omeros	OMER	0.9071	0.0128	0.0001	0.8815	0.9196	60000	0	Healthcare
05/24/2006	Vonage Holdings	VG	0.9067	0.0127	0.0001	0.8810	0.9191	805000	150000	Telecommunications
04/10/2014	Adamas Pharmaceuticals	ADMS	0.9045	0.0127	0.0001	0.8789	0.9169	10000	0	Healthcare
07/24/2014	Pfenex	PFNX	0.8964	0.0127	0.0001	0.8711	0.9087	180000	0	Healthcare
05/03/1999	CONSOL Energy	CNX	0.8891	0.0126	0.0001	0.8640	0.9014	550000	226250	Materials
05/02/2014	SCYNEXIS	SCYX	0.8799	0.0124	0.0001	0.8550	0.8920	40000	0	Healthcare
09/29/2005	Avalon Pharmaceuticals	AVRX	0.8763	0.0123	0.0001	0.8515	0.8883	120000	0	Healthcare
06/27/2007	AuthenTec	AUTH	0.8711	0.0123	0.0001	0.8465	0.8831	36000	0	High Technology
02/05/2014	Genocea Biosciences	GNCA	0.8639	0.0122	0.0001	0.8395	0.8758	110000	0	Healthcare
10/12/2009	RailAmerica	RA	0.8639	0.0122	0.0001	0.8395	0.8758	120000	51635	Industrials
07/29/2010	Molycorp	MCP	0.8629	0.0121	0.0001	0.8385	0.8747	290000	0	Materials
07/25/2007	Rex Energy	REXX	0.8600	0.0121	0.0001	0.8357	0.8718	80000	0	Energy and Power
06/18/2010	Motricity	MOTR	0.8553	0.0120	0.0001	0.8311	0.8670	40000	0	High Technology
10/03/2012	LifeLock	LOCK	0.8526	0.0120	0.0001	0.8285	0.8643	240000	0	High Technology
11/15/2006	Emergent BioSolutions	EBS	0.8461	0.0119	0.0001	0.8222	0.8577	2000000	300000	Healthcare
10/25/2013	Endurance Intl Grp Hldg	EIGI	0.8447	0.0119	0.0001	0.8208	0.8563	120000	0	High Technology
05/15/2007	Continental Resources	CLR	0.8424	0.0119	0.0001	0.8186	0.8539	60000	0	Energy and Power
02/01/2012	US Silica Holdings	SLCA	0.8415	0.0118	0.0001	0.8177	0.8530	20000	0	Materials
03/22/2013	West Corp	WSTC	0.8397	0.0119	0.0001	0.8160	0.8513	40000	0	Consumer Products and Services
10/04/2012	Berry Plastics Group	BERY	0.8335	0.0118	0.0001	0.8099	0.8449	160000	0	Materials
11/18/2011	Intermolecular	IMI	0.8335	0.0118	0.0001	0.8099	0.8449	30000	0	High Technology
05/15/2007	Pinnacle Gas Resources	PINN	0.8297	0.0117	0.0001	0.8062	0.8411	20000	0	Energy and Power
07/24/2013	Heat Biologics	HTBX	0.8276	0.0116	0.0001	0.8042	0.8389	20000	0	Healthcare
03/29/2011	Apollo Global Management	APO	0.8268	0.0116	0.0001	0.8034	0.8381	932984	118100	Financials
	mean		*0.8758*	*0.0123*	*0.0001*	*0.8510*	*0.8878*	*257466.1333*	*31032.8333*	
	std		*0.0400*	*0.0006*	*0.0000*	*0.0389*	*0.0406*	*460060.5601*	*73961.0203*	
	min		*0.8268*	*0.0116*	*0.0001*	*0.8034*	*0.8381*	*10000.0000*	*0.0000*	
	max		*0.9861*	*0.0139*	*0.0002*	*0.9583*	*0.9997*	*2000000.0000*	*300000.0000*	
12/15/2004	Las Vegas Sands	LVS	0.4932	0.0070	0.0000	0.4793	0.5000	60000	0	Media and Entertainment
10/06/1999	PlanetRx.com	PLRX	0.4873	0.0069	0.0000	0.4736	0.4940	30000	0	Retail
12/19/2007	Orion Energy Systems	OESX	0.4808	0.0068	0.0000	0.4672	0.4874	100000	0	Industrials
07/18/2014	SAGE Therapeutics	SAGE	0.4735	0.0067	0.0000	0.4601	0.4800	70000	0	Healthcare
05/17/1999	Nextcard	NXCD	0.4727	0.0067	0.0000	0.4593	0.4792	20000	0	Financials
03/09/2005	International Sec Exchange	ISE	0.4689	0.0066	0.0000	0.4556	0.4753	0	6000	Financials
12/12/2013	Kindred Biosciences	KIN	0.4638	0.0066	0.0000	0.4507	0.4702	1940000	0	Healthcare

11/07/2013	Twitter	TWTR	0.4585	0.0065	0.0000	0.4455	0.4648	90000	0	High Technology
07/24/2013	Agios Pharmaceuticals	AGIO	0.4556	0.0065	0.0000	0.4428	0.4619	40000	0	Healthcare
07/20/2011	Zillow	Z	0.4427	0.0063	0.0000	0.4302	0.4488	40000	0	High Technology
09/20/2013	FireEye	FEYE	0.4398	0.0063	0.0000	0.4274	0.4459	120000	0	High Technology
01/30/1998	VeriSign	VRSN	0.4348	0.0061	0.0000	0.4225	0.4407	60000	0	High Technology
03/23/1998	ISS Group	ISSX	0.4314	0.0061	0.0000	0.4192	0.4373	80000	0	High Technology
09/25/2013	Foundation Medicine	FMI	0.4032	0.0057	0.0000	0.3918	0.4087	80000	0	Healthcare
09/20/2007	athenahealth	ATHN	0.4015	0.0057	0.0000	0.3902	0.4071	40000	0	High Technology
08/18/2000	WJ Communications	WJCI	0.3928	0.0056	0.0000	0.3817	0.3982	0	1500	High Technology
02/25/2000	DigitalThink	DTHK	0.3823	0.0054	0.0000	0.3715	0.3876	40000	0	Consumer Products and Services
02/25/2000	Intersil Holding	ISIL	0.3666	0.0052	0.0000	0.3563	0.3717	80000	0	High Technology
11/19/2014	Second Sight Med Prod	EYES	0.3568	0.0051	0.0000	0.3468	0.3617	10000	0	Healthcare
07/22/1999	MP3.COM	MPPP	0.3501	0.0050	0.0000	0.3402	0.3549	40000	0	High Technology
07/27/2000	Corvis	CORV	0.3364	0.0048	0.0000	0.3269	0.3410	40000	0	Telecommunications
07/20/1999	Engage Technologies	ENGA	0.2897	0.0041	0.0000	0.2815	0.2937	20000	0	High Technology
07/28/1999	drugstore.com	DSCM	0.2835	0.0041	0.0000	0.2755	0.2874	140000	0	Retail
12/03/1998	Ticketmaster Online-CitySearch	TMCS	0.2754	0.0039	0.0000	0.2676	0.2792	36000	0	High Technology
04/07/1999	Rhythms NetConnections	RTHM	0.2404	0.0035	0.0000	0.2337	0.2438	20000	0	Telecommunications
07/17/1998	Broadcast.Com	BCST	0.2270	0.0033	0.0000	0.2206	0.2301	20000	0	High Technology
12/01/1999	McAfee.com	MCAF	0.2159	0.0031	0.0000	0.2098	0.2189	20000	0	High Technology
02/10/1999	Healtheon	HLTH	0.2018	0.0029	0.0000	0.1961	0.2046	30000	0	Healthcare
03/29/1999	priceline.com	PCLN	0.1836	0.0026	0.0000	0.1784	0.1861	80000	0	High Technology
12/10/1999	Freemarkets	FMKT	0.1356	0.0020	0.0000	0.1318	0.1375	80000	0	Consumer Products and Services
	mean		*0.3682*	*0.0052*	*0.0000*	*0.3578*	*0.3733*	*114200.0000*	*250.0000*	
	std		*0.1051*	*0.0015*	*0.0000*	*0.1022*	*0.1066*	*346576.6970*	*1119.9600*	
	min		*0.1356*	*0.0020*	*0.0000*	*0.1318*	*0.1375*	*0.0000*	*0.0000*	
	max		*0.4932*	*0.0070*	*0.0000*	*0.4793*	*0.5000*	*1940000.0000*	*6000.0000*	

Table 6
Bootstrap efficiency analysis- 379 IPOs: top and worst performers (VRS assumption)

We present the top and worst 30 IPOs of the full sample (379 IPOs) in terms of their ability to minimize underpricing. We sort the IPOs based on their bootstrap efficiency performance under the VRS assumption in order to account for differences between sectors. High bootstrap efficiency levels indicate high IPO performance. Additionally, we identify the IPO firm's sector alongside with the lobby and PAC donation amounts. Also we present the 95% bootstrapped confidence intervals of the estimations alongside with the estimated bias and its standard deviation. Finally, the main descriptive statistics are tabulated below each IPO group.

Listing Date	Company	Ticker	Bias Corrected VRS	Estimated Bias	STD of the estimated Bias	Lower Bound	Upper Bound	Lobby Money	PAC Money	Sector
11/08/2007	ICx Technologies	ICXT	0.9684	0.0316	0.0002	0.9440	0.9956	1420000	85000	High Technology
05/10/2013	BioAmber	BIOA	0.9553	0.0274	0.0003	0.9224	0.9792	80000	0	Materials
02/03/2004	TRW Automotive Holdings	TRW	0.9518	0.0128	0.0001	0.9301	0.9636	0	675000	Industrials
04/10/2014	Ally Financial	ALLY	0.9458	0.0093	0.0000	0.9295	0.9541	2110000	0	Financials
04/12/2012	Oaktree Capital Group	OAK	0.9455	0.0545	0.0008	0.9080	0.9902	260000	0	Financials
10/28/2009	Addus HomeCare	ADUS	0.9454	0.0261	0.0003	0.9131	0.9681	40000	0	Healthcare
05/05/2005	Lazard	LAZ	0.9453	0.0092	0.0000	0.9289	0.9536	290000	0	Financials
05/24/2006	Vonage Holdings	VG	0.9399	0.0136	0.0001	0.9202	0.9525	805000	150000	Telecommunications
07/30/1999	Biopure	BPUR	0.9324	0.0202	0.0002	0.9068	0.9497	20000	0	Healthcare
06/12/2001	Kraft Foods	KFT	0.9321	0.0191	0.0002	0.9060	0.9499	0	59500	Consumer Staples
05/18/2012	Facebook	FB	0.9309	0.0385	0.0005	0.8973	0.9662	1350000	270000	High Technology
06/19/2001	The Princeton Review	REVU	0.9263	0.0207	0.0002	0.9001	0.9441	60000	0	Consumer Products and Services
03/08/2007	Clearwire	CLWR	0.9248	0.0095	0.0001	0.9077	0.9335	80000	0	High Technology
04/23/2008	American Water Works	AWK	0.9240	0.0073	0.0000	0.9115	0.9305	300000	100000	Energy and Power
03/22/2013	West Corp	WSTC	0.9233	0.0072	0.0000	0.9110	0.9298	40000	0	Consumer Products and Services
04/10/2014	Adamas Pharmaceuticals	ADMS	0.9201	0.0177	0.0001	0.8981	0.9365	10000	0	Healthcare
10/08/2009	Omeros	OMER	0.9192	0.0235	0.0002	0.8887	0.9399	60000	0	Healthcare
11/17/2011	Delphi Automotive	DLPH	0.9188	0.0074	0.0000	0.9060	0.9253	396429	40500	Industrials
05/03/1999	CONSOL Energy	CNX	0.9099	0.0160	0.0001	0.8888	0.9247	550000	226250	Materials
12/13/2013	Cheniere Energy Partners	CQH	0.9093	0.0071	0.0000	0.8972	0.9156	2630000	201800	Energy and Power
12/09/2004	Foundation Coal Holdings	FCL	0.9041	0.0074	0.0000	0.8913	0.9106	0	74000	Materials
11/18/2010	General Motors	GM	0.9032	0.0262	0.0003	0.8748	0.9274	9570000	284500	Industrials
03/29/2011	Apollo Global Management	APO	0.9022	0.0073	0.0000	0.8896	0.9088	932984	118100	Financials
03/09/2011	HCA Holdings	HCA	0.9015	0.0185	0.0002	0.8762	0.9187	200000	268250	Healthcare
11/15/2007	EnergySolutions	ES	0.9014	0.0081	0.0000	0.8874	0.9086	1020000	780000	Energy and Power
02/11/2011	Kinder Morgan	KMI	0.9006	0.0186	0.0002	0.8753	0.9179	190000	0	Energy and Power
06/10/2004	CB Richard Ellis Group	CBG	0.8963	0.0072	0.0000	0.8839	0.9027	10000	0	Real Estate
05/02/2014	SCYNEXIS	SCYX	0.8908	0.0215	0.0002	0.8628	0.9096	40000	0	Healthcare
02/01/2012	US Silica Holdings	SLCA	0.8908	0.0096	0.0000	0.8751	0.8996	20000	0	Materials
03/15/2012	Allison Transmission Hldg	ALSN	0.8887	0.0082	0.0000	0.8745	0.8960	240000	0	Industrials
	mean		*0.9216*	*0.0170*	*0.0001*	*0.9002*	*0.9368*	*757480.4333*	*111096.6667*	
	std		*0.0215*	*0.0110*	*0.0002*	*0.0199*	*0.0267*	*1790773.6903*	*192603.8139*	
	min		*0.8887*	*0.0071*	*0.0000*	*0.8628*	*0.8960*	*0.0000*	*0.0000*	
	max		*0.9684*	*0.0545*	*0.0008*	*0.9440*	*0.9956*	*9570000.0000*	*780000.0000*	
07/18/2014	SAGE Therapeutics	SAGE	0.5562	0.0104	0.0001	0.5413	0.5658	70000	0	Healthcare
03/09/2005	International Sec Exchange	ISE	0.5510	0.0107	0.0001	0.5360	0.5609	0	6000	Financials
11/07/2013	Twitter	TWTR	0.5487	0.0314	0.0003	0.5256	0.5756	90000	0	High Technology
12/19/2007	Orion Energy Systems	OESX	0.5412	0.0044	0.0000	0.5336	0.5451	100000	0	Industrials
07/24/2013	Agios Pharmaceuticals	AGIO	0.5366	0.0114	0.0001	0.5213	0.5472	40000	0	Healthcare
06/17/1998	software.net	SWNT	0.5354	0.0145	0.0001	0.5218	0.5482	20000	0	High Technology
12/13/2012	SolarCity	SCTY	0.5338	0.0136	0.0001	0.5196	0.5459	230000	2000	Industrials

05/29/2014	Resonant	RESN	0.5284	0.0125	0.0001	0.5120	0.5393	40000	0	High Technology
07/20/2011	Zillow	Z	0.5236	0.0176	0.0001	0.5062	0.5397	40000	0	High Technology
09/20/2013	FireEye	FEYE	0.5204	0.0178	0.0001	0.5030	0.5367	120000	0	High Technology
03/23/1998	ISS Group	ISSX	0.5095	0.0249	0.0002	0.4895	0.5316	80000	0	High Technology
01/30/1998	VeriSign	VRSN	0.5022	0.0057	0.0000	0.4922	0.5074	60000	0	High Technology
09/25/2013	Foundation Medicine	FMI	0.4768	0.0154	0.0001	0.4612	0.4911	80000	0	Healthcare
09/20/2007	athenahealth	ATHN	0.4748	0.0156	0.0001	0.4592	0.4892	40000	0	High Technology
08/18/2000	WJ Communications	WJCI	0.4633	0.0110	0.0001	0.4495	0.4734	0	1500	High Technology
12/12/2013	Kindred Biosciences	KIN	0.4601	0.0121	0.0000	0.4479	0.4708	1940000	0	Healthcare
02/25/2000	Intersil Holding	ISIL	0.4554	0.0308	0.0003	0.4349	0.4810	80000	0	High Technology
02/25/2000	DigitalThink	DTHK	0.4477	0.0074	0.0000	0.4365	0.4546	40000	0	Consumer Products and Services
07/22/1999	MP3.COM	MPPP	0.4448	0.0366	0.0004	0.4238	0.4777	40000	0	High Technology
07/27/2000	Corvis	CORV	0.4212	0.0674	0.0010	0.4037	0.4811	40000	0	Telecommunications
12/10/1999	Freemarkets	FMKT	0.3988	0.0960	0.0026	0.3821	0.4880	80000	0	Consumer Products and Services
11/19/2014	Second Sight Med Prod	EYES	0.3967	0.0031	0.0000	0.3913	0.3995	10000	0	Healthcare
07/28/1999	drugstore.com	DSCM	0.3479	0.0217	0.0001	0.3324	0.3660	140000	0	Retail
07/20/1999	Engage Technologies	ENGA	0.3418	0.0176	0.0001	0.3284	0.3571	20000	0	High Technology
12/03/1998	Ticketmaster Online-CitySearch	TMCS	0.3252	0.0158	0.0001	0.3124	0.3392	36000	0	High Technology
04/07/1999	Rhythms NetConnections	RTHM	0.3072	0.0294	0.0003	0.2923	0.3340	20000	0	Telecommunications
07/17/1998	Broadcast.Com	BCST	0.2881	0.0235	0.0002	0.2747	0.3093	20000	0	High Technology
12/01/1999	McAfee.com	MCAF	0.2568	0.0148	0.0001	0.2462	0.2693	20000	0	High Technology
02/10/1999	Healtheon	HLTH	0.2376	0.0052	0.0000	0.2308	0.2423	30000	0	Healthcare
03/29/1999	priceline.com	PCLN	0.2344	0.0224	0.0002	0.2231	0.2548	80000	0	High Technology
	mean		*0.4389*	*0.0207*	*0.0002*	*0.4244*	*0.4574*	*120200.0000*	*316.6667*	
	std		*0.1020*	*0.0189*	*0.0005*	*0.1005*	*0.1012*	*346964.9093*	*1163.2545*	
	min		*0.2344*	*0.0031*	*0.0000*	*0.2231*	*0.2423*	*0.0000*	*0.0000*	
	max		*0.5562*	*0.0960*	*0.0026*	*0.5413*	*0.5756*	*1940000.0000*	*6000.0000*	

Table 7 presents the bias-corrected results under the CRS assumption for the top and lowest 30 IPOs of the reduced sample (excluding overpriced IPOs, N=317). With a slightly broader scope than the respective full sample group, the highest performers now include IPOs from 9 sectors (Consumer Staples, Energy and Power, Financials, Healthcare, High Technology, Industrials, Materials, Media and Entertainment and Telecommunications), whereas the group of the lowest performers comprises 8 sectors (Consumer Products and Services, Financials, Healthcare, High Technology, Industrials, Media and Entertainment, Retail and Telecommunications). In addition, the top 30 performers have a mean bias-corrected efficiency score of 0.9993; the statistic for the lowest 30 is 0.4647. Again, PAC donors and companies that complement lobbying with PAC campaigns appear more likely to be listed within the top 30 rather than in the bottom group.

Under the VRS assumption (Table 8), the group of the highest performers includes IPOs from 10 sectors (Consumer Staples, Energy and Power, Financials, Healthcare, High Technology, Industrials, Materials, Media and Entertainment, Retail and Telecommunications), whereas the bottom group is associated with 7 sectors (Consumer Products and Services, Financials, Healthcare, High Technology, Industrials, Retail, and Telecommunications). On average, the top 30 performers exhibit a bias-corrected efficiency score of 0.9969; the lowest 30 a score of 0.4809. Invariably, the top group outnumbers the bottom one in firms donating PAC money with 12 and 4 IPOs, respectively. It becomes also evident that the lowest efficiency levels systematically relate to High Technology. Overall, the bias-corrected results for both samples and returns to scale assumptions lend strong support to our baseline findings.

Table 7
Bootstrap efficiency analysis- 317 IPOs: top and worst performers
(CRS assumption)

We present the top and worst 30 IPOs of the reduced sample (317 IPOs) in terms of their ability to minimize underpricing. We sort the IPOs based on their bootstrap efficiency performance under the CRS assumption. High bootstrap efficiency levels indicate high IPO performance. Additionally, we identify the IPO firm's sector alongside with the lobby and PAC donation amounts. Also we present the 95% bootstrap confidence intervals of the estimations alongside with the estimated bias and its standard deviation. Finally, the main descriptive statistics are tabulated below each IPO group.

Listing Date	Company	Ticker	Bias Corrected CRS	Estimated Bias	STD of the estimated Bias	Lower Bound	Upper Bound	Lobby Money	PAC Money	Sector
07/31/2014	Marinus Pharmaceuticals	MRNS	0.9994	0.0006	0.0000	0.9977	1.0001	40000	0	Healthcare
12/12/2013	Kindred Biosciences	KIN	0.9994	0.0006	0.0000	0.9977	1.0001	1940000	0	Healthcare
03/20/2013	Tetraphase Pharmaceuticals	TTPH	0.9994	0.0006	0.0000	0.9977	1.0001	60000	0	Healthcare
08/03/2010	Trius Therapeutics	TSRX	0.9994	0.0006	0.0000	0.9977	1.0001	60000	0	Healthcare
11/16/2007	Internet Brands	INET	0.9994	0.0006	0.0000	0.9977	1.0001	80000	0	High Technology
02/09/2007	VeriChip	CHIP	0.9994	0.0006	0.0000	0.9977	1.0001	120000	0	Telecommunications
08/05/2004	RightNow Technologies	RNOW	0.9994	0.0006	0.0000	0.9977	1.0001	110000	0	High Technology
06/24/2011	KiOR	KIOR	0.9994	0.0006	0.0000	0.9977	1.0001	120000	0	Energy and Power
12/17/2010	Fortegra Financial	FRF	0.9994	0.0006	0.0000	0.9977	1.0001	150000	0	Financials
11/19/2010	Aeroflex Holding	ARX	0.9994	0.0006	0.0000	0.9977	1.0001	8700	0	High Technology
04/22/2010	Codexis	CDXS	0.9994	0.0006	0.0000	0.9977	1.0001	190000	0	Materials
12/14/2006	NewStar Financial	NEWS	0.9994	0.0006	0.0000	0.9977	1.0001	0	15000	Financials
11/02/2005	Cbeyond Communications	CBEY	0.9994	0.0006	0.0000	0.9977	1.0001	100000	0	Telecommunications
08/17/2005	Rockwood Holdings	ROC	0.9994	0.0006	0.0000	0.9977	1.0001	140000	0	Materials
06/14/2005	Premium Standard Farms	PORK	0.9994	0.0006	0.0000	0.9977	1.0001	40000	18075	Consumer Staples
02/10/2005	Nasdaq Stock Market	NDAQ	0.9994	0.0006	0.0000	0.9977	1.0001	0	51400	Financials
01/21/2005	ViaCell	VIAC	0.9994	0.0006	0.0000	0.9977	1.0001	20000	0	Healthcare
07/30/2004	EnerSys	ENS	0.9994	0.0006	0.0000	0.9977	1.0001	0	150000	High Technology

05/24/2004	Genworth Financial	GNW	0.9994	0.0006	0.0000	0.9977	1.0001	180000	0	Financials
08/02/2001	Bunge	BG	0.9994	0.0006	0.0000	0.9977	1.0001	120000	0	Consumer Staples
03/15/2001	SureBeam Corp(Titan Corp)	SURE	0.9994	0.0006	0.0000	0.9977	1.0001	220000	500	Industrials
07/29/1999	Lennox International	LII	0.9994	0.0006	0.0000	0.9977	1.0001	0	8000	Industrials
07/28/1999	American National Can Group	CAN	0.9994	0.0006	0.0000	0.9977	1.0001	0	7300	Materials
07/22/1998	USEC	USU	0.9994	0.0006	0.0000	0.9977	1.0001	60000	0	Materials
05/27/1998	Capstar Broadcasting	CRB	0.9994	0.0006	0.0000	0.9977	1.0001	60000	0	Media and Entertainment
05/11/1998	MGC Communications	MGCX	0.9994	0.0006	0.0000	0.9977	1.0001	0	5500	Telecommunications
06/12/2001	Kraft Foods	KFT	0.9994	0.0006	0.0000	0.9977	1.0001	0	59500	Consumer Staples
11/15/2007	EnergySolutions	ES	0.9988	0.0007	0.0000	0.9971	0.9995	1020000	780000	Energy and Power
10/01/2014	Vivint Solar	VSLR	0.9986	0.0007	0.0000	0.9969	0.9993	40000	0	Energy and Power
05/28/2004	Alnylam Pharmaceuticals	ALNY	0.9977	0.0006	0.0000	0.9960	0.9983	40000	0	Healthcare
	mean		*0.9993*	*0.0006*	*0.0000*	*0.9976*	*1.0000*	*163956.6667*	*36509.1667*	
	std		*0.0004*	*0.0000*	*0.0000*	*0.0004*	*0.0004*	*382799.2196*	*143574.3383*	
	min		*0.9977*	*0.0006*	*0.0000*	*0.9960*	*0.9983*	*0.0000*	*0.0000*	
	max		*0.9994*	*0.0007*	*0.0000*	*0.9977*	*1.0001*	*1940000.0000*	*780000.0000*	
12/15/2004	Las Vegas Sands	LVS	0.6224	0.0004	0.0000	0.6213	0.6228	60000	0	Media and Entertainment
10/06/1999	PlanetRx.com	PLRX	0.6149	0.0004	0.0000	0.6138	0.6153	30000	0	Retail
12/19/2007	Orion Energy Systems	OESX	0.6066	0.0005	0.0000	0.6056	0.6070	100000	0	Industrials
07/18/2014	SAGE Therapeutics	SAGE	0.5976	0.0004	0.0000	0.5966	0.5980	70000	0	Healthcare
05/17/1999	Nextcard	NXCD	0.5966	0.0004	0.0000	0.5956	0.5970	20000	0	Financials
03/09/2005	International Sec Exchange	ISE	0.5917	0.0004	0.0000	0.5907	0.5921	0	6000	Financials
12/12/2013	ARAMARK Holdings	ARMK	0.5853	0.0004	0.0000	0.5843	0.5857	200000	2000	Retail
11/07/2013	Twitter	TWTR	0.5786	0.0004	0.0000	0.5776	0.5790	90000	0	High Technology
07/24/2013	Agios Pharmaceuticals	AGIO	0.5750	0.0004	0.0000	0.5740	0.5754	40000	0	Healthcare
07/20/2011	Zillow	Z	0.5587	0.0004	0.0000	0.5578	0.5591	40000	0	High Technology
09/20/2013	FireEye	FEYE	0.5551	0.0004	0.0000	0.5542	0.5555	120000	0	High Technology
01/30/1998	VeriSign	VRSN	0.5487	0.0003	0.0000	0.5477	0.5490	60000	0	High Technology
03/23/1998	ISS Group	ISSX	0.5445	0.0003	0.0000	0.5435	0.5448	80000	0	High Technology
09/25/2013	Foundation Medicine	FMI	0.5087	0.0004	0.0000	0.5078	0.5090	80000	0	Healthcare
09/20/2007	athenahealth	ATHN	0.5067	0.0003	0.0000	0.5058	0.5070	40000	0	High Technology
08/18/2000	WJ Communications	WJCI	0.4958	0.0003	0.0000	0.4949	0.4961	0	1500	High Technology
02/25/2000	DigitalThink	DTHK	0.4824	0.0003	0.0000	0.4815	0.4827	40000	0	Consumer Products and Services
02/25/2000	Intersil Holding	ISIL	0.4626	0.0003	0.0000	0.4618	0.4629	80000	0	High Technology
11/19/2014	Second Sight Med Prod	EYES	0.4503	0.0003	0.0000	0.4495	0.4506	10000	0	Healthcare
07/22/1999	MP3.COM	MPPP	0.4419	0.0003	0.0000	0.4411	0.4422	40000	0	High Technology
07/27/2000	Corvis	CORV	0.4246	0.0003	0.0000	0.4239	0.4249	40000	0	Telecommunications
07/20/1999	Genentech	DNA	0.3655	0.0003	0.0000	0.3649	0.3658	1040000	5000	Healthcare
07/28/1999	drugstore.com	DSCM	0.3580	0.0002	0.0000	0.3574	0.3582	140000	0	Retail
12/03/1998	Ticketmaster Online-CitySearch	TMCS	0.3476	0.0002	0.0000	0.3470	0.3478	36000	0	High Technology
04/07/1999	Rhythms NetConnections	RTHM	0.3034	0.0003	0.0000	0.3029	0.3036	20000	0	Telecommunications
07/17/1998	Broadcast.Com	BCST	0.2866	0.0002	0.0000	0.2861	0.2868	20000	0	High Technology
12/01/1999	McAfee.com	MCAF	0.2725	0.0002	0.0000	0.2720	0.2727	20000	0	High Technology
02/10/1999	Healtheon	HLTH	0.2547	0.0002	0.0000	0.2543	0.2549	30000	0	Healthcare
03/29/1999	priceline.com	PCLN	0.2316	0.0002	0.0000	0.2312	0.2317	80000	0	High Technology
12/10/1999	Freemarkets	FMKT	0.1713	0.0001	0.0000	0.1710	0.1714	80000	0	Consumer Products and Services
	mean		*0.4647*	*0.0003*	*0.0000*	*0.4639*	*0.4650*	*90200.0000*	*483.3333*	
	std		*0.1327*	*0.0001*	*0.0000*	*0.1324*	*0.1327*	*184588.5266*	*1441.2838*	
	min		*0.1713*	*0.0001*	*0.0000*	*0.1710*	*0.1714*	*0.0000*	*0.0000*	
	max		*0.6224*	*0.0005*	*0.0000*	*0.6213*	*0.6228*	*1040000.0000*	*6000.0000*	

Table 8
Bootstrap efficiency analysis- 317 IPOs: top and worst performers (VRS assumption)

We present the top and worst 30 IPOs of the reduced sample (317 IPOs) in terms of their ability to minimize underpricing. We sort the IPOs based on their bootstrap efficiency performance under the VRS assumption in order to account for differences between sectors. High bootstrap efficiency levels indicate high IPO performance. Additionally, we identify the IPO firm's sector alongside with the lobby and PAC donation amounts. Also, we present the 95% bootstrap confidence intervals of the estimations alongside with the estimated bias and its standard deviation. Finally, the main descriptive statistics are tabulated below each IPO group.

Listing Date	Company	Ticker	Bias Corrected VRS	Estimated Bias	STD of the estimated Bias	Lower Bound	Upper Bound	Lobby Money	PAC Money	Sector
07/28/1999	American National Can Group	CAN	0.9988	0.0012	0.0000	0.9964	0.9999	0	7300	Materials
05/11/1998	MGC Communications	MGCX	0.9988	0.0012	0.0000	0.9964	0.9999	0	5500	Telecommunications
07/29/1999	Lennox International	LII	0.9988	0.0012	0.0000	0.9962	0.9999	0	8000	Industrials
05/27/1998	Capstar Broadcasting	CRB	0.9988	0.0012	0.0000	0.9962	0.9999	60000	0	Media and Entertainment
02/10/2005	Nasdaq Stock Market	NDAQ	0.9988	0.0012	0.0000	0.9963	0.9999	0	51400	Financials
01/21/2005	ViaCell	VIAC	0.9988	0.0012	0.0000	0.9963	0.9999	20000	0	Healthcare
08/02/2001	Bunge	BG	0.9988	0.0012	0.0000	0.9963	0.9999	120000	0	Consumer Staples
08/17/2005	Rockwood Holdings	ROC	0.9987	0.0013	0.0000	0.9960	0.9999	140000	0	Materials
05/24/2004	Genworth Financial	GNW	0.9987	0.0013	0.0000	0.9960	0.9999	180000	0	Financials
06/24/2011	KiOR	KIOR	0.9987	0.0013	0.0000	0.9960	0.9999	120000	0	Energy and Power
04/22/2010	Codexis	CDXS	0.9987	0.0013	0.0000	0.9960	0.9999	190000	0	Materials
07/22/1998	USEC	USU	0.9985	0.0015	0.0000	0.9954	0.9999	60000	0	Materials
11/19/2010	Aeroflex Holding	ARX	0.9983	0.0017	0.0000	0.9949	0.9999	8700	0	High Technology
10/01/2014	Vivint Solar	VSLR	0.9980	0.0013	0.0000	0.9955	0.9991	40000	0	Energy and Power
06/14/2005	Premium Standard Farms	PORK	0.9980	0.0020	0.0000	0.9938	0.9998	40000	18075	Consumer Staples
07/30/2004	EnerSys	ENS	0.9980	0.0020	0.0000	0.9938	0.9998	0	150000	High Technology
11/02/2005	Cbeyond Communications	CBEY	0.9977	0.0023	0.0000	0.9930	0.9998	100000	0	Telecommunications
11/15/2007	EnergySolutions	ES	0.9977	0.0018	0.0000	0.9941	0.9994	1020000	780000	Energy and Power
12/17/2010	Fortegra Financial	FRF	0.9970	0.0030	0.0000	0.9906	0.9998	150000	0	Financials
05/22/2002	Liquidmetal Technologies	LQMT	0.9967	0.0013	0.0000	0.9940	0.9979	120000	0	Materials
12/14/2006	NewStar Financial	NEWS	0.9960	0.0040	0.0000	0.9872	0.9997	0	15000	Financials
03/15/2001	SureBeam Corp(Titan Corp)	SURE	0.9960	0.0040	0.0000	0.9872	0.9997	220000	500	Industrials
06/22/2011	Vanguard Health Systems	VHS	0.9960	0.0012	0.0000	0.9935	0.9971	120000	123000	Healthcare
12/11/2009	KAR Auction Services	KAR	0.9952	0.0023	0.0000	0.9906	0.9973	53000	0	Retail
05/23/2002	Eon Labs	ELAB	0.9952	0.0014	0.0000	0.9925	0.9964	20000	0	Healthcare
06/29/1999	Seminis	SMNS	0.9947	0.0013	0.0000	0.9920	0.9959	20000	0	Consumer Staples
06/12/2001	Kraft Foods	KFT	0.9930	0.0070	0.0000	0.9828	0.9991	0	59500	Consumer Staples
02/05/1998	Vysis (BP Amoco)	VYSI	0.9927	0.0023	0.0000	0.9882	0.9948	3520000	172000	Healthcare
02/02/2007	Molecular Insight Pharm	MIPI	0.9921	0.0015	0.0000	0.9891	0.9935	105000	0	Healthcare
07/31/2014	Marinus Pharmaceuticals	MRNS	0.9906	0.0094	0.0001	0.9710	0.9996	40000	0	Healthcare
	mean		*0.9969*	*0.0022*	*0.0000*	*0.9926*	*0.9989*	*215556.6667*	*46342.5000*	
	std		*0.0023*	*0.0018*	*0.0000*	*0.0054*	*0.0017*	*651009.0151*	*145988.4131*	
	min		*0.9906*	*0.0012*	*0.0000*	*0.9710*	*0.9935*	*0.0000*	*0.0000*	
	max		*0.9988*	*0.0094*	*0.0001*	*0.9964*	*0.9999*	*3520000.0000*	*780000.0000*	
02/08/2007	Accuray	ARAY	0.6295	0.0027	0.0000	0.6250	0.6320	200000	0	Healthcare
10/06/1999	PlanetRx.com	PLRX	0.6135	0.0018	0.0000	0.6103	0.6151	30000	0	Retail
12/19/2007	Orion Energy Systems	OESX	0.6061	0.0010	0.0000	0.6043	0.6070	100000	0	Industrials
11/07/2013	Twitter	TWTR	0.5968	0.0071	0.0000	0.5861	0.6032	90000	0	High Technology
07/18/2014	SAGE Therapeutics	SAGE	0.5945	0.0035	0.0000	0.5891	0.5977	70000	0	Healthcare
05/17/1999	Nextcard	NXCD	0.5928	0.0056	0.0000	0.5854	0.5977	20000	0	Financials
03/09/2005	International Sec Exchange	ISE	0.5884	0.0037	0.0000	0.5829	0.5917	0	6000	Financials

12/12/2013	ARAMARK Holdings Corp	ARMK	0.5843	0.0014	0.0000	0.5815	0.5855	200000	2000	Retail
07/24/2013	Agios Pharmaceuticals	AGIO	0.5715	0.0041	0.0000	0.5655	0.5750	40000	0	Healthcare
07/20/2011	Zillow	Z	0.5544	0.0071	0.0000	0.5457	0.5607	40000	0	High Technology
09/20/2013	FireEye	FEYE	0.5506	0.0074	0.0000	0.5420	0.5571	120000	0	High Technology
01/30/1998	VeriSign	VRSN	0.5476	0.0014	0.0000	0.5450	0.5489	60000	0	High Technology
03/23/1998	ISS Group	ISSX	0.5474	0.0077	0.0000	0.5374	0.5544	80000	0	High Technology
09/25/2013	Foundation Medicine	FMI	0.5049	0.0062	0.0000	0.4973	0.5105	80000	0	Healthcare
09/20/2007	athenahealth	ATHN	0.5027	0.0063	0.0000	0.4950	0.5083	40000	0	High Technology
02/25/2000	Intersil Holding	ISIL	0.4932	0.0074	0.0000	0.4809	0.4997	80000	0	High Technology
08/18/2000	WJ Communications	WJCI	0.4927	0.0040	0.0000	0.4873	0.4961	0	1500	High Technology
07/22/1999	MP3.COM	MPPP	0.4819	0.0095	0.0001	0.4650	0.4906	40000	0	High Technology
02/25/2000	DigitalThink	DTHK	0.4804	0.0023	0.0000	0.4766	0.4825	40000	0	Consumer Products and Services
07/27/2000	Corvis	CORV	0.4646	0.0273	0.0004	0.4304	0.4905	40000	0	Telecommunications
12/10/1999	Freemarkets	FMKT	0.4505	0.0443	0.0017	0.4015	0.4936	80000	0	Consumer Products and Services
11/19/2014	Second Sight Med Prod	EYES	0.4499	0.0007	0.0000	0.4487	0.4505	10000	0	Healthcare
07/28/1999	drugstore.com	DSCM	0.3773	0.0049	0.0000	0.3692	0.3816	140000	0	Retail
07/20/1999	Genentech	DNA	0.3692	0.0049	0.0000	0.3624	0.3737	1040000	5000	Healthcare
12/03/1998	Ticketmaster Online-CitySearch	TMCS	0.3491	0.0050	0.0000	0.3427	0.3536	36000	0	High Technology
04/07/1999	Rhythms NetConnections	RTHM	0.3337	0.0084	0.0000	0.3203	0.3416	20000	0	Telecommunications
07/17/1998	Broadcast.Com	BCST	0.3121	0.0061	0.0000	0.3013	0.3177	20000	0	High Technology
12/01/1999	McAfee.com	MCAF	0.2798	0.0034	0.0000	0.2748	0.2829	20000	0	High Technology
03/29/1999	priceline.com	PCLN	0.2546	0.0064	0.0000	0.2444	0.2606	80000	0	High Technology
02/10/1999	Healtheon	HLTH	0.2531	0.0019	0.0000	0.2504	0.2547	30000	0	Healthcare
	mean		*0.4809*	*0.0068*	*0.0001*	*0.4716*	*0.4872*	*94866.6667*	*483.3333*	
	std		*0.1147*	*0.0085*	*0.0003*	*0.1164*	*0.1142*	*185565.8138*	*1441.2838*	
	min		*0.2531*	*0.0007*	*0.0000*	*0.2444*	*0.2547*	*0.0000*	*0.0000*	
	max		*0.6295*	*0.0443*	*0.0017*	*0.6250*	*0.6320*	*1040000.0000*	*6000.0000*	

VII. Conclusion

Political connections formed via monetary contributions constitute a potentially powerful mechanism for reducing IPO underpricing. To evaluate this proposition, we require that the methodological tools in the pertinent literature be upgraded. Our contribution, in this respect, is twofold. First, we show how historical shortcomings of IPO performance assessment can be overcome through the application of a relative efficiency measure in a probabilistic framework. Having resolved the problem of comparability among IPO returns, we subsequently analyze the influence of lobbying and PAC contributions in a fully nonparametric manner.

We find a robustly positive effect of PAC money on IPO efficiency levels whereas the effect of lobbying is more nuanced. Our sector analysis pinpoints circumstances under which contributions intensity can not only squander corporate cash but also impair efficiency levels. The

implications for prospective issuers are clear: political donations do not constitute a one-size-fits-all solution but can be effective when the distinct type of connectedness reinforces the firm's position within its competitive environment, as with the lobbying contributions of Energy and Power firms.

Overall, there are unique patterns for each economic sector but a common theme emerges in the important nonlinearities in the relationship of political contributions with IPO efficiency. On this basis, the nonparametric frontier analysis offers a decisive advantage by allowing the effects to unfold in an unbiased manner. Finally, although our interest here is in IPOs, the approach is more generally applicable in finance where relationships of influence are suspected.

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