Available online at www.sciencedirect.com
SCIENCE DIRECT
ELSEVIER
Journal of Financial Economics 73 (2004) 375–407
JOURNAL OF Financial ECONOMICS
www.elsevier.com/locate/econbase

Grandstanding, certification and the underpricing of venture capital backed IPOs ☆

Peggy M. Lee, Sunil Wahal*

Goizueta Business School, Emory University, Atlanta, GA 30322-2710, USA

Received 15 November 2002; accepted 4 September 2003

Abstract

We examine the role of venture capital backing in the underpricing of IPOs. Controlling for endogeneity in the receipt of venture funding, we find that venture capital backed IPOs experience *larger* first-day returns than comparable non-venture backed IPOs. Between 1980 and 2000, the average return difference ranges from 5.01 percentage points to 10.32 percentage points. This return difference is particularly pronounced in the "bubble" period of 1999–2000. Consistent with the grandstanding hypothesis proposed by Gompers (J. Financial Econon. 42 (1996) 133), we find that higher underpricing leads to larger future flows of capital into venture capital funds, particularly after 1996. Cross-sectionally, the effect of underpricing is attenuated for younger venture capital firms and those that have previously conducted fewer IPOs.

JEL classification: G32; G24

Keywords: Venture Capital; IPOs

1. Introduction

In this paper, we examine the role of venture capital backing in the underpricing of initial public offerings (IPOs). We are not the first to conduct such an investigation.

☆We thank Jay Ritter for providing IPO data and Alexander Ljungqvist for providing supplemental information on firm founding dates. Daniel Silver provided able research assistance and Ron Harris provided excellent computational assistance. We thank an anonymous referee, Dave Denis, Diane Denis, Yael Hochberg, Bill Megginson, Jay Ritter, and participants at the EVI conference at Yale University, the Western Finance Association meetings in Cabo San Lucas, and at the SMS conference in Paris for helpful comments and suggestions.

*Corresponding author.
E-mail address: sunil_wahal@bus.emory.edu (S. Wahal).

0304-405X/$ - see front matter
doi:10.1016/j.jfineco.2003.09.003

The pioneering efforts in this literature are due to Megginson and Weiss (1991) and Barry et al. (1990). Megginson and Weiss compare venture capital (VC) backed IPOs to non-VC backed IPOs matched by industry and offering size between January 1983 and September 1987. They find that the first-day returns of VC backed IPOs are significantly lower than those of non-VC backed IPOs.[1] They argue that their results are consistent with the intuitively plausible idea that venture capitalists certify the true value of the firm and therefore reduce underpricing. Barry et al. focus on the monitoring role of venture capitalists in IPOs between 1978 and 1987 and find that the ownership, the length of board service, and the number of venture capitalists invested in the pre-IPO firm are negatively related to IPO underpricing. Based on this correlation, they conclude that venture capitalists are ‘‘recognized by capital markets through lower underpricing for IPOs with better monitors’’ (p. 447).

Since the publication of these two studies, a stream of research seeking to understand the provision of venture financing has emerged.[2] Sahlman (1990) reports that ‘‘although a typical large venture capital firm receives up to 1,000 proposals each year, it invests in only a dozen or so new companies’’ (p. 475). Kaplan and Stromberg (2002) use unique data to describe the due diligence and analyses conducted by venture capitalists prior to the provision of financing. They show how the characteristics of and risks inherent in entrepreneurial ventures translate into specific contractual provisions with entrepreneurs. Other studies characterize the contracting environment between entrepreneurs and venture capitalists as one in which the provision of venture financing is linked to the allocation of cash flow and control rights (Sahlman, 1990; Gompers and Lerner, 1996; Black and Gilson, 1998; Hellman, 1998; Kaplan and Stromberg 2001, 2002). Such allocations take place through covenants on securities exchanged for cash, in the distribution of ownership and voting rights, and in the assignment of board seats. Both the ex ante analyses conducted by venture capitalists, and the contracts designed to mitigate information and agency problems, suggest that venture financing represents an endogenous choice made by entrepreneurs and venture capitalists – the receipt of venture funding is the outcome of protracted negotiations between venture capitalists and entrepreneurs.

This choice is reflected in the nonrandom distribution and characteristics of VC backed IPOs. We examine a sample of over 6,413 IPOs between 1980 and 2000, of which over 37% (2,383) are VC backed. VC backed IPOs show significant clustering across both industry and geographical dimensions. We find that venture financing is disproportionately provided to firms in technology-intensive industries, particularly software and commercial biological research. Consistent with the results of Lerner (1995) and Gompers and Lerner (1998), over 50% of all venture backed IPO firms in

[1] As is conventional in the IPO literature, we use the terms underpricing and first-day return interchangeably.

[2] Perhaps not coincidently, the volume of venture financing has also increased dramatically over this period. Gompers and Lerner (2001) report that commitments to the venture capital industry increased from approximately $4 billion in 1990 to almost $68 billion in 1999 (both figures in 1999 dollars), representing a compounded annual growth rate of 33%. They also report similar large increases in the frequency and dollar value of VC backed IPOs.

our sample are headquartered in California, Massachusetts, and Texas, states with high concentrations of venture capitalists. We also find differences in the characteristics of firms taken public by venture capitalists. Venture capitalists generally take smaller and younger firms public. These firms have lower revenues than non-VC backed firms and are less likely to be profitable. On average, VC backed IPOs employ higher quality underwriters but raise less cash than non-VC backed IPOs.

Our interest is in the underpricing of VC backed IPOs. In an ideal world, we would want to observe underpricing for a VC backed IPO and the underpricing that the same IPO would experience had it *not* received venture financing. This would allow us to make causal inferences about the effect of venture backing on IPO underpricing. Unfortunately, given the nonexperimental nature of the data, what we actually observe is the underpricing for a VC backed IPO and the underpricing for a non-VC backed IPO. If the provision of venture financing were random, one could simply compute differences between the first-day returns of VC backed and non-VC backed IPOs. The traditional approach would be to match VC backed IPOs to non-VC backed IPOs based on a set of characteristics and attribute the difference in underpricing to venture backing, or to estimate OLS regressions with a dummy variable for VC backing. Using such regressions, Bradley and Jordan (2002) conclude that once they control for industry effects and underwriter quality, there is no difference in underpricing between VC backed and non-VC backed IPOs. Gompers and Lerner (1997) question the certification hypothesis and show that the underpricing differential between VC backed and non-VC backed IPOs is sensitive to both estimation periods and methodologies. Although controls are undeniably important, the crux of our problem is that venture backing is not randomly distributed, but represents an endogenous choice. This introduces a selectivity bias, one that can easily reverse inferences.[3]

To account for this bias, we use matching methods that endogenize the receipt of venture financing and do not impose linearity or function form restrictions (see, for example, Rubin, 1974, 1977; Rosenbaum and Rubin, 1983; Dehejia and Wahba, 1999). The basic intuition behind these procedures is to use a first-stage regression to predict the receipt of venture funding. Estimates from this first-stage regression are then fed into various methods of matching non-VC backed IPOs to VC backed IPOs. Addressing the endogeneity issue directly produces results that are strikingly different from earlier empirical studies. Over the entire sample period, the average first-day return of VC backed IPOs is *larger* than non-venture backed IPOs. The return difference ranges from a minimum of 5.0 percentage points to a maximum of 10.3 percentage points, with standard errors of 1.8 and 2.1 percentage points respectively. These return differentials are statistically significant and economically

[3] LaLonde (1986) shows that conventional econometric techniques that ignore the endogenous choice problem yield substantially different (and incorrect) estimates from methods that explicitly recognize selectivity. More recently, Ackerberg and Botticini (2002) show that endogenous contract choices between landlords and tenants in Renaissance Tuscany can significantly influence coefficients on variables that proxy for risk aversion.

important. The average underpricing of all IPOs over the sample period is about 18.0%. Using the smallest estimate (5.0 percentage points), the underpricing differential as a proportion of total underpricing is 28.0%.

Because there is pronounced non-stationarity in the volume and underpricing of IPOs (Ritter and Welch, 2002; Loughran and Ritter, 2002a), we examine the underpricing differential over various subperiods. In particular, it is possible that our results are entirely due to the internet bubble period of 1999–2000. We find that the average underpricing differential between VC backed and non-VC backed IPOs is 25.0 percentage points in 1999–2000 and 2.0 percentage points in 1980–1998, with standard errors of approximately 9.9 and 1.0 percentage points respectively. Again, the underpricing differential is statistically significant and economically important in both subperiods. The average underpricing of IPOs in 1980–1998 is 11.0%. Therefore, the 2.0 percentage point differential represents almost 20% of total underpricing. Another way to assess the economic magnitude of these return differentials is to calculate the incremental amount of money left on the table in VC backed IPOs. Loughran and Ritter (2002b) calculate this amount as the number of shares issued multiplied by the difference between the closing price on the first day of trading and the offer price. Using their metric, the average amount of money left on the table for non-VC backed IPOs in our sample is $27 million. The average first-day return for the non-VC backed IPOs is 13.4%. Again, using our smallest estimate of the return differential (5.0 percentage points), this implies an additional $10 million left on the table by VC backed IPOs. Even excluding the bubble period, similar calculations suggest an additional $4 million left on the table.

Venture capitalists typically retain a large fraction of their equity holdings subsequent to an IPO; Megginson and Weiss (1991) report that on average, venture capitalists own 36.6% of the firm prior to the IPO and 26.3% immediately thereafter. Greater underpricing represents a real cost to the venture capital fund because there is a transfer of wealth to new shareholders. Why would venture capitalists bear this cost? It is possible that the first-day return differentials are due to our inability to perfectly account for endogeneity and for differences between VC backed and non-VC backed firms. While no endogeneity correction or system of controls is perfect, our results are robust to a variety of specifications.

One explanation is that venture capitalists receive some quid pro quo for leaving more money on the table. It is possible that underwriters preferentially allocate shares of other underpriced IPOs to venture capital firms in exchange for greater underpricing in the VC's own portfolio firm. Loughran and Ritter (2002a) provide examples in which VC firms were allocated hot IPOs that were subsequently flipped for immediate profits. Recent legal investigations into IPO practices also support this scenario (see, for example, "Something ventured, something gained?," *Wall Street Journal*, 10/17/2002). However, such activity occurred largely in 1999 and 2000. The underpricing differential appears in earlier periods as well. Therefore, we doubt that such quid pro quo arrangements can explain our results.

A more likely explanation lies in the grandstanding hypothesis proposed by Gompers (1996). Venture capital firms create limited partnerships ("venture capital funds") to raise and invest capital. These funds have finite lives, typically ten years, after which they must liquidate their investments and return money to the original providers (institutional investors such as pension funds and endowments). Although VC firms can realize returns through acquisitions as well as IPOs of their portfolio firms, the majority of returns are created by taking companies public. Because of this, establishing a reputation as a VC firm that is capable of taking portfolio companies public is critical to future fundraising. Gompers (1996) describes examples in which VC firms that are unable to take portfolio companies public are unable to raise future capital. He also describes converse examples of VC firms that, once they take a portfolio company public, are quickly able to raise additional capital. Since establishing reputation is critical to future fundraising, VC firms are willing to bear the cost of underpricing because taking a company public signals quality. Gompers (1996) argues that cross-sectionally, fundraising is less of a problem for older VC firms because their reputations are already established. In contrast, less-established VC firms need to signal quality by taking portfolio companies public. As a result, they are more willing to bear the cost of higher underpricing. Consistent with this argument, he finds that younger VC firms grandstand by taking younger companies public and allowing greater underpricing. This enables young VC firms to raise more capital in the future than they would otherwise. If grandstanding is responsible for our results, then underpricing should have a larger effect on the fundraising ability of low-reputation VC firms. Also, such VC firms should be more likely to take smaller and younger companies public.

To determine if these effects are present in our data, we first create two subsamples of VC-backed IPOs with different definitions for the "lead" VC firm in the IPO. Specifically, we identify the lead venture capital firm as the VC firm with the earliest investment, or the VC firm with the largest investment. We then estimate fundraising regressions similar to Gompers (1996) for both subsamples. The dependent variable in these regressions is the size of the next fund raised by the lead VC firm after the IPO. The primary independent variables of interest are proxies for VC reputation (VC age and the number of previous IPOs done by the VC), IPO underpricing, and interaction effects of reputation proxies with underpricing.

The regressions show that the flow of capital into the lead VC firm is positively related to VC age and the number of previous IPOs done by the VC firm. This indicates that more-reputable venture capital firms are able to raise more money. The future flow of capital is also positively related to underpricing, implying that there is a benefit to bearing the cost of underpricing. Most important, the interaction effects between VC age and underpricing, and between the number of prior IPOs and underpricing, are negative. Consistent with grandstanding, this suggests that underpricing has a larger effect on the ability of young VC firms, or those that have done fewer IPOs, to raise future capital. Since the grandstanding explanation also predicts that low-reputation VC firms are more likely to take smaller and younger companies public, we also estimate regressions of both measures of reputation on IPO characteristics. We find that younger VC firms, and those that have previously done fewer IPOs, tend to take smaller and younger companies public.

There is a marked increase in the number of new firms entering the venture capital industry in the late 1990s, roughly corresponding to the increase in IPO activity. Aggregate data show that on average, 33 new firms entered the industry annually between 1980 and 1996. Between 1997 and 2000, this more than tripled to 106 new firms entering the industry every year. If the entry of new firms increases competition, there may be a change in the willingness of incumbent firms to bear the cost of underpricing to raise further capital. We estimate fundraising regressions for the 1980–1996 and 1997–2000 subperiods separately and find that the sensitivity of future capital flows to underpricing is higher in the later subperiod. Interestingly, the interaction effects between reputation and underpricing are significant in both periods, suggesting that the cross-sectional effects have not changed.

These results favor the grandstanding explanation. However, we also consider other explanations. Gompers (1996) describes the "recycling hypothesis" as one in which investors in venture capital firms plough their profits from earlier funds back into new funds raised by the same venture capital firms. However, the recycling hypothesis does not explain why some VC firms would receive more capital, or why underpricing would have larger effects for low-reputation VC firms. Another possibility is a prospect theory explanation advanced by Loughran and Ritter (2002b). Under their explanation, issuers ignore the wealth loss from underpricing because they sum this wealth loss with the wealth gain from the IPO itself. This implies that the positive relation between underpricing and future capital flows could simply be an IPO effect, rather than an underpricing effect. To separate the two effects, we compile a sample of all venture capital firms that are in existence in a given year for the 21-year period. This sample includes both VC firms that took a company public and those that did not. We then estimate two-stage Heckman selection regressions that account for the fact that underpricing is only observed when a company is taken public. The first-stage regression predicts whether a VC firm does an IPO in that year and feeds into a second-stage regression that models capital inflows as a function of IPO underpricing. The coefficient on IPO underpricing is positive and significant in the second-stage regression, implying that underpricing has a positive effect on future capital inflows, even after correcting for the observability bias.

Taken together, the evidence suggests that the grandstanding behavior originally documented by Gompers (1996) plays an important role in describing the costs that venture capitalists are willing to bear in taking their portfolio companies public. The remainder of the paper proceeds as follows. Section 2 describes our data and sample construction. Section 3 describes the methodological approach and provides the basic underpricing results. Section 4 describes the capital flow regressions. Section 5 describes various robustness checks and examines alternative explanations. Section 6 concludes.

2. Data

Our sample of IPOs comes from data provided by Jay Ritter. This dataset includes accumulated corrections made by him to IPO data from a variety of sources. The data include offering dates, offering prices, file price ranges, closing prices, SIC codes, and underwriter rankings. Underwriter rankings are based on an amended version of the Carter and Manaster (1990) and Carter et al. (1998) rankings and are described in Loughran and Ritter (2002a). The rankings range in value from 0 to 9, with higher values indicating higher quality rankings. Also included is a dummy variable that identifies VC backed IPOs and a second dummy variable that identifies internet-related firms. Unit offerings and IPOs with an offer price of less than $5.00 are not included. This database contains 6,997 IPOs between 1980 and 2000. We eliminate IPOs without valid cusip numbers, perm numbers, and underwriter rankings, resulting in a sample of 6,413 IPOs over the 21-year period.

We supplement this IPO database with information from the new issues database of Securities Data Corporation (SDC). For each IPO, we collect information on net proceeds, the number of shares in the offering, the book value of equity per share prior to the offering, revenue just after the offering, earnings per share up to two years prior to the offering, the firm's total assets prior to the offering, founding date, and the state in which the firm is headquartered.

As reported by other researchers, there are missing value problems associated with several of these data items. Founding dates are missing in SDC for approximately 75% of our sample. We update information on firm founding dates for 25% of the sample from data provided by Alexander Ljungqvist; data collection procedures employed by him are described in Ljungqvist and Wilhelm (2003). Thus, age information is available for approximately 50% of the IPOs in our sample. Missing value problems are also significant for earnings per share. Since sample sizes shrink when we use these data, we report results both with and without these data items.

In addition to IPO and firm-level information, our tests also require specific information about venture capital investment in these firms. We obtain supplemental data on VC participation from the Venture Economics data obtained through SDC. The Venture Economics database has been extensively described and analyzed by Lerner (1994, 1995), Gompers (1995, 1996), and Gompers and Lerner (1998). From this database, we collect information on the number of venture capital firms with an investment in each IPO at the time of the offering, the round dates and dollar value of each investment, the founding date and size of each venture capital firm, and the amount of capital raised by each venture capital firm in the calendar year following the IPO.

Some of our capital flow regressions require us to build a database of VC firms in existence each year. This requires knowledge of founding dates, mergers, consolidations, name changes, and other such events that can influence the existence of a venture capital firm in any given year. Such data items are frequently not available, and when they are, they are notoriously "dirty." To bypass some of these problems, we start with a listing of all venture capital firms in existence in 2003. Venture Economics lists the fundraising status of each firm in one of four categories: actively seeking new investment, inactive/unknown, reducing investment activity, and making few, if any, new investments. In many cases, Venture Economics also leaves this field blank. We regard the VC firm as being "alive" if it is actively seeking new investments. If the status field is missing or is labeled "inactive/unknown," *and* if the venture firm has not made any investments in the last five years, we regard the firm as being "dead." This information is accurate as of 2003 but unfortunately Venture Economics does not maintain information on historical status. Therefore, we build the database recursively using paper sources. To do this, we take the 2003 database and check every entry against historical records in annual issues of *Pratt's Guide to Venture Capital Sources* going back to 1980. *Pratt's Guide* lists VC firms in existence in each year and provides basic descriptive information about each firm, such as founding date, funds under management, etc.

3. Results

3.1. Unadjusted first-day returns

Table 1 shows the number of IPOs and average first-day returns. First-day returns are calculated as the percentage price movement from the offering price to the closing price on the first day of trading. For VC backed IPOs, we present raw first-day returns, and first-day returns of matched non-VC backed IPOs using a methodology similar to Megginson and Weiss (1991). (The returns for non-matched, non-VC backed IPOs are not shown in the table.) Each VC backed IPO is matched with a (single) non-VC backed IPO in the same three-digit SIC code and closest in

Table 1
Unadjusted first-day returns for VC backed and "matched" non-VC backed IPOs
First-day returns are calculated as the percentage change in price from the offer price to the closing price of the stock on the first day of trading. For VC backed IPOs, raw first-day returns are presented. For non-VC backed IPOs, only "matched" returns are presented. Following Megginson and Weiss (1991), each VC backed IPO is matched with a (single) non-VC backed IPO in the same three-digit SIC code and with the closest net proceeds. In addition, the matching procedure also requires that the non-VC backed IPO take place between two years before and two years after the VC backed IPO. Statistics are presented for the full sample of IPOs from 1980 to 2000, the Megginson and Weiss (1991) sample (MW) from 1983 to September 1987, a "partial" Barry (1990) sample from 1980 to 1987, and for various subperiods.

Sample	VC backed IPOs		Non-VC backed IPOs		
	Number of IPOs	First-day return	"Matched" first-day return	Return difference	*T*-statistic
Full sample (1980–2000)	2,208	26.82	19.36	7.45	5.99
MW sample (1983–1987)	314	6.72	8.20	−1.48	1.12
BMPV sample (1980–1987)	402	7.66	8.91	−1.25	0.62
Subperiods					
1980–1989	471	7.89	8.50	−0.61	0.62
1990–1998	1,304	16.17	16.70	−0.53	0.54
1999	238	88.93	42.02	46.90	6.17
2000	194	67.89	35.70	32.19	4.63
1980–1998	1,775	13.97	14.53	−0.55	0.72

net proceeds. However, their sample period is from January 1983 to September 1987. In our longer period, an exact replication of their matching procedure could potentially match VC backed IPOs with non-VC backed IPOs 20 years apart. Therefore, our modified matching procedure also requires that the non-VC backed IPO take place within two years of the VC backed IPO. The table shows average return differences between the VC backed IPOs and matched non-VC backed IPOs and associated *t*-statistics.

The average first-day return of VC backed IPOs is 26.8% versus 19.4% for matched non-VC backed IPOs – a difference of over seven percentage points with a *t*-statistic of 5.9. Thus, at first blush, a longer time series suggests that VC backing of IPOs is associated with *higher*, rather than lower, underpricing. This appears inconsistent with the results of Megginson and Weiss, so we attempt to replicate their sample. To do so, we retain all observations in which the offering date is between January 1983 and September 1987. This produces a subsample of 314 IPOs. For this subsample, the average return difference between VC backed and non-VC backed IPOs is −1.5 percentage points with a *t*-statistic of 1.1. By way of comparison, Megginson and Weiss (1991) document an average return difference of −4.8 percentage points with a *t*-statistic of 3.6 in a sample of 320 IPOs. The discrepancy between Megginson and Weiss's results and our modified replication could be due to two reasons. First, Megginson and Weiss (1991, footnote 5) report that due to a large concentration of VC backed firms in the Office, Computing & Accounting Machines industry as well as the Electronic Components & Accessories industry, they include 18 non-VC backed IPOs priced at less than $5, or offering amounts less than $3 million (which otherwise serve as data exclusionary criteria). We do not include such IPOs. Second, as mentioned above, our matching procedure is slightly different from theirs in that we require that the matched IPO take place between two years before and two years after the VC backed IPO. Megginson and Weiss do not employ such a restriction.

Table 1 also reports average underpricing for a subsample that represents a partial overlap with Barry et al. (1990). Barry et al.'s sample consists of IPOs between 1978 and 1987. Since our sample period starts in 1980, we construct a partially overlapping subsample of IPOs between 1980 and 1987. For this subsample, the average return difference is −1.3 percentage points with a *t*-statistic of 0.6. This result, in conjunction with those of the Megginson and Weiss subsample, suggests time-series instability in the differences between first-day returns of VC backed and non-VC backed IPOs. Ritter and Welch (2002) suggest that many IPO phenomena are nonstationary. Therefore, we also present first-day returns for various subperiods. In the decade of the 1980s, the first-day return difference between VC backed and non-VC backed IPOs is −0.6 percentage points (*t*-statistic = 0.6). In the 1990s (but excluding 1999), the return difference is very similar in magnitude and significance (−0.5 percentage points with a *t*-statistic of 0.5). However, as with many IPO phenomena, 1999 and 2000 are fundamentally different. For 1999, the average first-day return for VC backed IPOs is 46.9 percentage points higher than for non-VC backed IPOs (*t*-statistic = 6.2). For 2000, the average return difference is 32.2 percentage points (*t*-statistic = 4.6). Thus, not only did average underpricing increase dramatically during 1999–2000, but return differentials based on the modified Megginson and Weiss (1991) benchmark also increased substantially. Excluding 1999–2000 from the sample, the average return difference between VC backed and non-VC backed IPOs drops to -0.6 percentage points and is statistically insignificant (t-statistic = 0.7).

3.2. Endogeneity: theory and evidence

As we argue in the introduction, the provision and receipt of venture funding represents the outcome of an endogenous choice by entrepreneurs and venture capitalists. Not all entrepreneurs desire venture financing and not all entrepreneurs receive it. Megginson and Weiss (1991) explicitly recognize this and state that "the cost and stringency of VC investment, as well as the sheer difficulty in obtaining it … implies that only those firms which would benefit most from the services venture capitalists provide will be willing and able to accept such participation" (p. 882). The choice is evident in the rich array of contracts designed to allocate cash flow and control rights in entrepreneurial firms (Sahlman, 1990; Gompers and Lerner, 1996; Black and Gilson, 1998; Hellman, 1998; Kaplan and Stromberg, 2001, 2002).

The endogenous choice is reflected not only in the provision of financing by venture capitalists but also in their eventual exit from the entrepreneurial venture. Nonrandom endogenous choices in the provision of financing are reflected in the nonrandom distribution and characteristics of VC backed IPOs. Panel A of Table 2 shows the industry distribution of VC backed IPOs across two-digit SIC codes that represent at least 1% of the sample (at least 23 IPOs). Across all industries, VC backed IPOs represent 37% of all IPOs. However, there is significant variation across industries, from a low of zero (in the Hotels and Lodging, SIC code 70) to a high of 58% (in Chemicals and Allied Products, SIC code 28). A χ^2 test rejects the null hypothesis of equality of distributions across industries with a p-value of 0.00. We also examine industries in which VC backed IPOs are concentrated in absolute rather than relative terms. We find large clusters in software firms (SIC code 7372) and firms conducting commercial biological research (SIC code 8731). The former represent 11% of all VC backed IPOs and the latter represent 3%.

In addition to industry clustering, our data also show geographic concentrations.[4] In Panel B, we show VC backed IPOs as a percentage of all IPOs for the state in which the firm is headquartered. We display this distribution only for states that represent at least 2% of all IPOs (at least 121 IPOs). Here, too, the data show large variation. For IPOs of firms headquartered in Florida, 20.9% are venture backed. The corresponding figures for California and Massachusetts are 56.8% and 60.7%. In fact, the largest number of VC backed IPOs emerge from three states: California (803), Massachusetts (246), and Texas (152). Collectively, these three states represent over 50% of all VC backed IPOs. This degree of concentration is not surprising. As Lerner (1995) shows, geographic distance adds to the cost of monitoring portfolio

[4] We thank Paul Gompers for suggesting an examination of geographic distributions.

Table 2

Distribution and characteristics of VC backed and non-VC backed IPOs

Panel A shows the distribution of VC backed IPOs across two-digit SIC codes. The percentage of VC backed IPOs as a proportion of all IPOs in that SIC code is shown. SIC codes in which there are less than 23 VC backed IPOs over the entire sample period are not shown (corresponding to 1% of all VC backed IPOs). Panel B shows the geographic distribution of VC backed IPOs. The percentage of VC backed IPOs as a proportion of all IPOs of firms headquartered in that state are shown. States with less than 121 IPOs, corresponding to 2% of all IPOs, are not shown. Panel C shows the time-series distribution of VC backed IPOs as a proportion of all IPOs for each calendar year. Panel D provides means of various characteristics of VC backed and non-VC backed IPOs, along with associated t-statistics. Net proceeds are in millions of dollars. Age is the average number of years from the founding date to the IPO date. The gross spread is in percent. The book value per share is in dollars prior to the offering date. Revenue per share is as of prior to the offering. The percentage of positive earnings per share (EPS) is from up to two years prior to the offering. Total assets are in millions of dollars prior to the offering.

2-digit SIC	Total number of IPOs	VC backed IPOs (%)	2-digit SIC	Total number of IPOs	VC backed IPOs (%)
Panel A: Industry distribution of VC backed IPOs					
13	135	17.8	49	89	22.4
15	32	9.4	50	185	25.4
20	82	26.8	51	99	14.1
22	35	20.0	53	42	26.1
23	46	6.5	54	44	18.1
25	24	12.5	56	67	28.3
26	34	44.1	57	63	28.5
27	72	20.8	58	130	19.2
28	336	58.0	59	152	35.5
30	41	7.3	61	107	13.1
32	26	23.0	62	67	7.4
33	72	20.8	63	148	13.5
34	60	16.7	65	28	14.3
35	398	53.5	67	76	2.6
36	556	50.0	70	52	0
37	102	17.6	73	1215	52.7
38	374	53.4	78	58	15.5
39	75	24.0	79	41	7.3
42	55	14.5	80	237	43.0
45	52	17.3	82	27	37.0
47	28	17.8	87	235	48.9
48	312	37.5	Full Sample	6413	37.1

State	Total number of IPOs	VC backed IPOs (%)	State	Total number of IPOs	VC backed IPOs (%)
Panel B: Geographic distribution of VC backed IPOs					
CA	1415	56.8	NJ	223	30.0
CO	128	36.7	NY	483	21.9
CT	145	35.1	OH	143	26.5
FL	282	20.9	PA	203	38.4
GA	162	38.9	TX	507	30.0
IL	222	30.6	VA	128	33.6
MA	405	60.7	WA	126	54.8
MN	129	44.1			

Table 2 (*continued*)

Year	Total number of IPOs	VC backed IPOs (%)	Year	Total number of IPOs	VC backed IPOs (%)
Panel C: Time-series distribution of VC backed IPOs					
1980	70	32.8	1991	273	50.1
1981	191	28.8	1992	386	47.1
1982	79	25.3	1993	484	45.6
1983	452	25.4	1994	389	33.6
1984	177	24.2	1995	432	42.8
1985	182	23.6	1996	659	39.9
1986	382	22.5	1997	481	25.9
1987	274	27.0	1998	293	26.3
1988	102	33.3	1999	495	54.1
1989	110	37.2	2000	396	53.5
1990	106	45.2			

	VC backed IPOs		Non-VC backed IPOs		
	Mean	*N*	Mean	*N*	*T*-statistic
Panel D: Characteristics of VC backed and non-VC backed IPOs					
Age	7.0	1159	14.7	1446	12.13
Book value	0.76	1961	6.63	3253	11.28
Revenue	19.9	1732	52.1	2759	3.16
EPS (% pos.)	49.7	806	76.5	1358	12.71
Total assets	104.4	1719	543.2	2628	3.97
Net proceeds	40.5	2286	58.3	3782	5.44
Underwriter rank	7.80	2383	6.79	4030	21.02
Gross spread	7.09	2285	7.36	3781	1.76

firms; naturally, venture capital firms invest in companies closer to their own operations.

It is well known that there are waves in IPO activity (see Ibbotson and Jaffe, 1975; Ritter, 1984; and more recently, Lowry and Schwert, 2002). This is also reflected in the time-series distribution of VC backed IPOs. Panel C of Table 2 shows the distribution of VC backed IPOs for each calendar year. On average, approximately 25–30% of all IPOs are VC backed. Most notable, however, is the dramatic increase in the percentage of VC backed IPOs in 1999–2000. In these two years, VC backed IPOs represent over 50% of all IPOs.

Finally, the fact that venture capitalists invest in particular types of firms is reflected in both firm and IPO characteristics. Panel D shows five firm-level characteristics for VC and non-VC backed IPOs prior to the offering: total assets (in $ millions), the book value of equity per share, revenue per share, the percentage of firms with positive earnings per share, and the age of the firm in months. VC backed IPOs take place in younger, smaller firms with lower book values of equity, lower revenues, and smaller assets. In addition, these firms are less likely to be profitable. The panel also shows the average net proceeds from the offering, the average underwriter rank, and the average gross spread. Consistent with Chen and Ritter (2000), gross spreads are approximately 7% and are not different between VC and non-VC backed IPOs. However, VC backed IPOs are generally smaller (average net proceeds are \$40.5 million compared to \$58.3 for non-VC backed IPOs, with a *t*-statistic of 5.4), and, on average, use higher quality underwriters (7.8 versus 6.7 with a *t*-statistic of 21.0).

3.3. Selection bias adjusted estimates

3.3.1. A methodological solution

Much of the descriptive evidence reported in Table 2 is not new. Gompers and Lerner (2000) and Megginson (2004) report similar industry and geographic concentrations, and Megginson and Weiss (1991), Barry et al. (1990), Gompers and Lerner (1997), and Bradley and Jordan (2002) report differences in characteristics of VC backed and non-VC backed IPOs. The nonrandomness of these data suggests that we can use this information to construct instruments that have some power in predicting the receipt of venture funding. There are also other good candidates for instruments. For example, Hellman and Puri (2002) report that VC backing is related to the adoption of stock option plans and the hiring of a marketing VP. However, such instruments require detailed data that we do not possess and that are not available from public sources.

The methodology that we employ accounts for endogenous choice in a matching framework, allowing causal inference in nonexperimental settings. Such methods are widely used in statistics and labor economics. Following the notation in Heckman et al. (1998), we define Y_1 as the one-day return for an IPO with VC backing, Y_0 as the one-day return for the same IPO without VC backing, and $D=1$ if the firm received VC backing (and zero otherwise). We are interested in Y_1–Y_0. However, this is unobservable for an individual firm because a firm either does or does not receive VC backing. The solution is to estimate the average effect of venture backing at the population level. We are interested in the average effect of VC backing on VC backed IPOs, $\mathrm{E}(Y_1 - Y_0|D = 1, X)$, where X is a vector of firm and/or industry characteristics. This could be estimated if we recognize the following condition:

$$\mathrm{E}(Y_1 - Y_0|D = 1, X) = \mathrm{E}(Y_1|D = 1, X) - \mathrm{E}(Y_0|D = 1, X). \tag{1}$$

$\mathrm{E}(Y_1|D = 1, X)$ is the average one-day return for VC backed IPOs. However, $\mathrm{E}(Y_0|D = 1, X)$, the average return VC backed IPOs *would* experience if they did not receive VC backing, is unavailable, at least in such nonexperimental data. The traditional approach is to use $\mathrm{E}(Y_0|D = 0, X)$, the average return of non-VC backed IPOs, instead. Unfortunately, because VC backing is not randomly assigned but represents an endogenous choice, this introduces a bias. This bias is formally defined as

$$B(X) = \mathrm{E}(Y_0|D=1, X) - \mathrm{E}(Y_0|D=0, X). \tag{2}$$

Rubin (1974, 1977) and Rosenbaum and Rubin (1983) show that under certain conditions, matching on $Pr(D=1|X)$ eliminates the bias and reduces the dimensionality of the problem. Specifically, Rosenbaum and Rubin propose the propensity score method as a way to implement matching while eliminating the bias. This method requires the estimation of a probit model for the endogenous choice variable ($D=1$ for VC backing, zero otherwise) with a vector of X variables. The predicted probability is then used as the propensity score and each VC backed IPO is matched with the non-VC backed IPO with the highest propensity score.

The propensity score method is an example of "nearest neighborhood" matching and is a one-to-one matching technique. It therefore discards data that are potentially valuable. It is also possible to match each VC backed IPO with more than one comparable non-VC backed IPO. Such one-to-many matching estimators fall under the rubric of "smoothed weighted matching estimators," and are proposed and implemented by Heckman et al. (1997, 1998). The intuition behind these is to use the weighted average of the outcomes of several (or perhaps all) non-VC backed IPOs. The weight given to each non-VC backed IPO is in proportion to the "closeness" of the vector of observables. We employ two versions of such one-to-many matching estimators. The first is a kernel estimator that uses a distribution to specify weights. We use a Gaussian kernel in our primary implementation but use other distributions as robustness checks (see Section 3.4.1). The second, known as regression-adjusted local linear matching, uses "local" weights (that is, it uses only part of the non-VC backed sample) and performs a local regression on X to estimate weights.

All matching is conducted with replacement. Using each matching estimator, we calculate the difference between the first-day return of a VC backed IPO and the matched first-day return of non-VC backed IPO(s). Rather than rely on assumed distributions of return differences, we use bootstrapped standard errors to conduct statistical inference. The bootstrapping is based on 50 replications. We also calculate selection-bias-adjusted 95% confidence intervals.

3.3.2. First-day return differences

Table 3 shows average selection-bias-adjusted first-day return differences between VC backed and non-VC backed IPOs using the propensity score method, the Gaussian kernel, and the regression-adjusted local linear method. Bootstrapped standard errors appear in parentheses and 95% confidence intervals are in square brackets.

The choice of instrumental variables used in the first stage of each method is critical to removing the selection bias. Given the industry and geographic concentrations of VC backed IPOs, SIC code and headquarter-state dummy variables are natural candidates. Time-series variation in IPOs, and the presence of "hot" markets, suggests that it is also important to control for calendar effects.

Table 3

Selection bias adjusted first-day return differences between VC backed and non-VC backed IPOs

The table presents selection bias adjusted average return differences between VC and non-VC backed IPOs, their standard errors and 95% confidence intervals. Each VC backed IPO is matched with one or many non-VC backed IPOs using the propensity score, Gaussian kernel, and regression-adjusted local linear matching approaches described in the text. Panel A uses the logarithm of net proceeds, two-digit SIC code dummies, calendar year dummies, headquarter-state dummies and underwriter ranks as instrumental variables in each matching approach. Panel B adds book value per share scaled by offering price, revenue per share scaled by offering price, and total assets per share scaled by offering price to the Panel A instruments. Panel C adds an earnings per share dummy variable (equal to one for positive earnings and zero otherwise) to the instruments in Panel B. For each matching approach, the table presents the average difference in first-day return of the VC backed and matched non-VC backed IPOs. Bootstrapped standard errors are based on 50 replications and appear in parentheses. Bias-adjusted 95% confidence intervals appear below the standard errors.

	Propensity score	Gaussian kernel	Regression-adjusted local linear
Panel A: Instrumental variables: log (net proceeds), SIC dummies, year dummies, headquarter-state dummies, underwriter rank			
Full sample	9.51	6.94	6.20
	(1.84)	(1.70)	(1.67)
	[7.89,12.56]	[3.39,10.54]	[3.75,9.88]
Subperiod: 1999–2000	25.52	32.05	32.83
	(9.93)	(9.30)	(8.17)
	[9.88,41.52]	[13.31,49.01]	[22.64,49.00]
Subperiod: 1980–1998	2.15	1.50	1.30
	(1.06)	(0.78)	(0.65)
	[0.53,3.70]	[−0.02,3.00]	[0.17,2.33]
Panel B: Instrumental variables: log (net proceeds), SIC dummies, year dummies, underwriter rank, headquarter-state dummies, book value per share scaled by offering price, revenue per share scaled by offering price, total assets per share scaled by offering price			
Full sample	8.45	10.32	9.46
	(2.37)	(2.06)	(2.50)
	[4.87,12.24]	[6.43,14.24]	[5.41,13.97]
Subperiod: 1999–2000	22.50	32.87	33.41
	(11.05)	(8.52)	(9.83)
	[8.06,31.72]	[11.89,47.30]	[12.45,48.06]
Subperiod: 1980–1998	2.62	1.99	1.89
	(1.23)	(0.94)	(0.74)
	[0.54,3.92]	[0.00,3.67]	[0.50,3.97]
Panel C: Instrumental variables: log (net proceeds), SIC dummies, year dummies, underwriter rank, headquarter-state dummies, book value per share scaled by offering price, revenue per share scaled by offering price, total assets per share scaled by offering price, EPS dummy			
Full sample	5.17	5.51	5.01
	(2.38)	(1.35)	(1.76)
	[0.27,9.96]	[3.04,8.45]	[1.19,7.55]
Subperiod: 1999–2000	NA	NA	NA
Subperiod: 1980–1998	2.19	2.86	2.66
	(1.05)	(1.16)	(1.48)
	[0.23,5.40]	[0.16,5.14]	[−0.30,5.36]

Beatty and Welch (1996) show that prior to 1990, prestigious underwriters were associated with lower underpricing but this effect may have reversed after 1990. To distinguish the effect of VC backing from investment banker (underwriter) quality, we use underwriter rank as an instrument. Since the results in Panel D of Table 2 show substantial differences in net proceeds, total assets, book value of equity, revenue, and profitability between VC backed and non-VC backed IPOs, we also use these variables as instruments.

Given the missing value problem associated with some of these data items, we present our results in three panels in which we incrementally add instruments that have missing data. Panel A presents our basic model in which we use the logarithm of net proceeds, two-digit SIC code dummies, calendar year dummies, headquarter-state dummies and underwriter rank in the first-stage regression. Most of these data items are non-missing and the estimates produced by these instruments are based on a relatively complete sample size (2,277 VC backed IPOs). The pseudo-R^2 of the first-stage regression is relatively high (0.22), suggesting that these instruments are good predictors of VC backing. (We do not display the first-stage regressions in the interest of conserving space.) In Panel B, we add book value per share scaled by offering price, revenue per share scaled by offering price, and total assets per share scaled by offering price to this basic model. The pseudo-R^2 increases marginally to 0.23, but the sample size drops to 1,490. Finally, in Panel C, we add a dummy variable equal to one if the firm has positive earnings per share and zero otherwise. This variable significantly increases the pseudo-R^2 to 0.28 but drastically decreases the sample size to 599.

Panel A shows that in the full sample, with the propensity score method, the average difference in first-day returns is 9.5 percentage points. The standard error of this estimate is 1.8% and the 95% confidence interval is between 7.9 and 12.6 percentage points. The average estimates using the Gaussian kernel and regression-adjusted local linear matching approach are somewhat lower (6.9 and 6.2 percentage points, respectively) but are still highly statistically significant (standard errors are approximately 1.7 percentage points for both methods). The estimates in Panel B range from a low of 8.4 to a high of 10.3 percentage points with standard errors of about 2 percentage points. The addition of earnings per share information in Panel C reduces the differential to approximately 5 percentage points but the estimate remains statistically significant. Since the estimates in Panel C are based on 599 observations, they are not directly comparable to those in Panels A and B.

Given the time-series variation in first-day returns documented in Table 1 and, in particular, the dramatically higher underpricing in 1999–2000, we also show separate estimates for the 1999–2000 and 1980–1998 subperiods. We do not calculate subperiod estimates by partitioning the full sample results because the latter are obtained from a first-stage regression that uses all the data. Instead, we reestimate the first-stage regression for each subperiod, thereby ‘‘tightening’’ the conditioning information and producing more conservative estimates. In Panel A, the average first-day return difference for 1999–2000 using the propensity score method is 25.5 percentage points. For the Gaussian kernel and regression-adjusted local linear matching method, the return differences are 32.0 and 32.8 percentage points, respectively. The standard errors of the estimates for this sample period are also higher (between 8 and 9 percentage points). The differentials remain statistically significant and the 95% confidence intervals do not include zero. The estimates in Panel B are similar. Adding earnings per share information in Panel C causes such a severe loss of observations in the subperiod 1999–2000 that we cannot produce estimates.

The average difference in underpricing between VC backed and non-VC backed IPOs is much smaller in 1980–1998. In Panel A, using the propensity score method, the average first-day return difference is 2.2 percentage points. The other estimators produce return differences of 1.5 and 1.3 percentage points. Note, however, that there is also a large decline in the standard errors associated with these differences. For example, the standard error of the 2.2 percentage point propensity score method estimate is 1.1 percentage points. The estimates in Panel B are generally larger and but with similar standard errors. In Panel C, for the 1980–1998 subperiod, the return differentials range from 2.1 to 2.86 percentage points with standard errors of approximately 1.0 percentage points. In general, the return differentials in the 1980–1998 are smaller, but remain statistically significant.

It is important to put the size of these estimates in economic terms. One way to do so is to compare the average return difference to average underpricing for all IPOs during that period. In the full sample, average underpricing is about 18%. Therefore, the first-day return differential of about 5 percentage points represents a significant portion (28%) of average underpricing. In 1999–2000, the average return differential of 25 percentage points represents 49% of total average underpricing over this period (which was 51%). Even in the 1980–1998 subperiod, where the underpricing differential between VC backed and non-VC backed IPOs shrinks to approximately 2 percentage points, this difference represents a large proportion (almost 20%) of average underpricing (11 percentage points).

3.4. *Robustness issues*

We perform a variety of checks to ensure that the first-day return differences between VC backed and non-VC backed IPOs are not driven by our choice of instrumental variables or specification of the estimator. We also consider an alternative methodology that addresses the endogeneity issue in a regression (rather than matching) framework. In the interest of brevity, these robustness checks do not appear in tables.

3.4.1. *Alternative specifications*

One problem with the instrumental variables used in the first-stage is that some of them possess a look-ahead property. Net proceeds and underwriter rank are only known at the time of the IPO, after the receipt of venture funding. In addition, our measure of revenues comes from after the offering. Given the dearth of good ex ante instruments for our problem, we continue to use these variables. Our motivation for doing so is that they are likely to be correlated with other ex ante but unobservable predictors, such as funding requirements by the firm. Nonetheless, we also produce results in which we incrementally drop these variables from the first-stage regression. Not surprisingly, the pseudo-R^2 of the first-stage regressions vary, but the underpricing differential remains large and statistically significant.

Since younger firms are more likely to receive VC funding, we also add firm age to the first-stage regression. Unfortunately, this reduces the sample size substantially. If we include firm age, the pseudo-R^2 of the first-stage regression increases to 0.24. The full-sample propensity score estimate is 13.3 percentage points, with a standard error of 4.7 percentage points, but the sample size is roughly halved. The subperiod results are also similar to those reported in Table 3.

We also determine if the choice of matching methods influences our conclusions. The Gaussian kernel, for instance, uses a normal distribution to assign weights to the non-VC backed IPOs. As an alternative, we also use the Epanechnikov kernel that assigns weights only if the matched IPOs are within a fixed distance (or "caliper") from the VC backed IPO. This and other similar matching methods leave our results qualitatively unchanged.

3.4.2. An alternative methodology

An alternative to the matching method is to employ a regression-based approach to correct for the endogenous choice. Known as endogenous switching regressions, this method is also a two-step procedure in which the first stage is the estimation of a probit regression that predicts the receipt of venture financing and the second stage (OLS) regression uses estimates from the first stage to provide consistent estimates of the parameters. Madalla (1983, p. 283) describes the basic econometrics of the procedure and an empirical application in finance can be found in Madhavan and Cheng (1997).

To implement this procedure, we use two-digit SIC code dummies, calendar year dummies, headquarter-state dummies, book value of equity per share scaled by offering price, revenue per share scaled by offering price, and total assets per share scaled by offering price as predictive variables in the first-stage regressions. The second-stage regression includes the logarithm of net proceeds, underwriter rankings, and a dummy variable equal to one if the offering is backed by a venture capitalist and zero otherwise. This last dummy variable is the regression-based difference in underpricing for VC versus non-VC backed IPOs. For the full sample, the first-stage regression has a pseudo-R^2 of 0.19. In the second-stage regression, the VC dummy variable has a coefficient of 0.43 with a t-statistic of 13.9. This implies that in the full sample, the first-day return of VC backed IPOs is 44 percentage points higher than for non-VC backed IPOs. The magnitude of the effect is larger than in the matching method and can be attributed to the fact that the selectivity correction λ has a coefficient of –0.23 with a t-statistic of 13.4. This indicates that not only is the selectivity correction important to the model, it also increases the (unconditional) return difference between VC backed and non-VC backed IPOs. If we include the earnings per share dummy variable in the first-stage regression, the coefficient on the VC dummy variable drops to 0.08 with a t-statistic of 3.3.

3.5. A different dependent variable

Information-based hypotheses of the effect of venture backing on the underpricing of IPOs are based on the idea that venture capitalists have a better understanding of the "true" value of the firm. In the certification hypothesis of Megginson and Weiss (1991), this information is credibly communicated to investment bankers pricing the IPO and results in lower underpricing of VC backed offerings. Therefore, it is possible that underpricing simply represents the wrong dependent variable. In other words, the true role of the VC firm is in establishing the offer price – relative to underlying value, not relative to an aftermarket price. If this is indeed the case, then the revision from the initial file price to the offer price should be smaller for VC backed offerings than for non-VC backed offerings.

To test this idea, we calculate, for each offering, the absolute return from the midpoint of the file price range to the offer price. We use the absolute return because under the null hypothesis that venture capitalists reduce information problems, the absolute (unsigned) price revision should be smaller. We then use this absolute return in the selection-bias-adjusted matching methods implemented in Table 3. The results of this analysis are presented in Table 4. Panels A, B, and C employ exactly the same instruments as those in Table 3. In Panel A, full sample estimates of return differentials range from a low of 2.3 percentage points to a high of 3.3 percentage points with standard errors of 0.8 and 0.6 percentage points, respectively. The estimates in Panels B and C are slightly higher. Clearly, price revisions are larger in VC backed IPOs than in non-VC backed IPOs. This is consistent with our earlier first-day return results, but inconsistent with information-based explanations of the role of venture capitalists in the underpricing of IPOs. Overall, our results appear robust across alternative methodologies, time periods, and conditioning information.

4. Explaining the underpricing differential

Venture capitalists are major shareholders in firms prior to an IPO, and typically retain some portion of their stakes following the IPO. Barry et al. (1990) report that the average VC holding in pre-IPO firms is 34.3%, and 24.6% immediately following the IPO. Comparable statistics reported by Megginson and Weiss (1991) are 36.6% and 26.3%, respectively. Therefore, higher first-day returns represent a real, *incremental* cost to venture capitalists because of the wealth transfer to new shareholders. Why would venture capital firms be willing to bear this incremental cost? We turn next to potential explanations of this phenomenon.

4.1. Institutional structure and grandstanding arguments

In order to understand the reasons why venture capitalists would bear the cost of underpricing, it is important to first understand the institutional structure of the venture capital industry. Most venture capital firms raise money in limited

Table 4
Selection bias adjusted differences between file price midpoint to offer price returns of VC backed and non-VC backed IPOs
For each IPO, a pre-IPO return is computed as the absolute value of the return from the midpoint of the file price range to the offer price. The table presents selection bias adjusted average pre-IPO return differences between VC and non-VC backed IPOs, their standard errors, and 95% confidence intervals. Each VC backed IPO is matched with one or many non-VC backed IPOs using the propensity score, Gaussian kernel, and regression-adjusted local linear matching approaches described in the text. Panel A uses the logarithm of net proceeds, two-digit SIC code dummies, calendar year dummies, headquarter-state dummies, and underwriter ranks as instrumental variables in each matching approach. Panel B adds book value per share scaled by offering price, revenue per share scaled by offering price, and total assets per share scaled by offering price to the Panel A instruments. Panel C adds an earnings per share dummy variable (equal to one for positive earnings and zero otherwise) to the instruments in Panel B. For each matching approach, the table presents the average difference in the pre-IPO return of the VC backed and matched non-VC backed IPOs. Bootstrapped standard errors are based on 50 replications and appear in parentheses. Bias-adjusted 95% confidence intervals appear below the standard errors.

	Propensity score	Gaussian kernel	Regression-adjusted local linear
Panel A: Instrumental variables: log (net proceeds), SIC dummies, year dummies, headquarter-state dummies, underwriter rank			
Full sample	2.32	3.34	3.15
	(0.79)	(0.58)	(0.72)
	[1.38,2.94]	[2.16,4.32]	[2.01,4.66]
Panel B: Instrumental variables: log (net proceeds), SIC dummies, year dummies, underwriter rank, headquarter-state dummies, book value per share scaled by offering price, revenue per share scaled by offering price, total assets per share scaled by offering price			
Full sample	2.84	3.69	3.47
	(1.00)	(0.89)	(0.90)
	[0.06,5.47]	[1.97,5.06]	[1.26,4.89]
Panel C: Instrumental variables: log (net proceeds), SIC dummies, year dummies, underwriter rank, headquarter-state dummies, book value per share scaled by offering price, revenue per share scaled by offering price, total assets per share scaled by offering price, EPS dummy			
Full sample	4.03	3.85	3.53
	(1.38)	(1.10)	(1.38)
	[−0.45,6.31]	[1.57,6.15]	[0.42,6.23]

partnerships, known as venture capital funds. Investors in these funds are typically institutions such as pension funds and endowments. Venture capital funds have fixed expirations, often ten years. Funds make investments in startup companies in the first four or five years, after which they proceed to harvest their investments. This is most often done by taking portfolio companies public, although in some cases the company can also be sold outright. The cash generated by this process is returned to the investors.

Since venture capital funds have fixed expirations, the venture capital firm must raise additional money in overlapping funds to stay in business. To do so, it must convince the limited partners that it is capable of selecting high-quality entrepreneurial investments and shepherding them through the IPO process. In other words, over time, it must establish a reputation of being able to take companies public. Therefore, one measure of reputation is the number of previous IPOs that the venture capital firm has conducted. The more experienced the venture capital firm is at taking portfolio companies public, the more comfortable the limited partners are likely to be in providing future funding. Gompers (1996) argues that venture firm age also effectively proxies for reputation because reputation effects are established over time and provides evidence to support this assertion.

Since establishing reputation is so important for future fundraising, venture capital firms are willing to bear the cost of underpricing because taking a company public signals quality. Cross-sectionally, venture capital firms that have not yet established a reputation (“low-reputation” firms) are likely to take smaller and younger companies public and bear the cost of even higher underpricing. In other words, the cross-sectional prediction of Gompers’s (1996) grandstanding hypothesis is that one should expect a negative correlation between venture firm reputation and underpricing. Venture firms that need to establish a reputation have more to gain by establishing their reputation and are willing to bear higher costs. This discussion suggests that regressions of future fundraising should show positive coefficients on measures of reputation (venture firm age and the number of previous IPOs conducted by the venture firm) and negative coefficients on the interaction of reputation and underpricing.

4.2. Basic grandstanding regressions

To test this explanation, we estimate capital flow regressions similar in spirit to Gompers (1996). We first obtain information on the identity and stakes of VC firms in VC backed IPOs from the Venture Economics database supplied by SDC. Often, more than one venture capital firm holds equity in the IPO firm. We use two methods to identify the “lead” venture capitalist. First, we follow Barry et al. (1990) and regard the VC firm with the largest stake in the pre-IPO firm as the lead venture capitalist. We identify the largest stake by cumulating the amount invested by the venture capitalist across all financing rounds. Second, we regard the first venture firm to provide funding as the lead VC firm.[5] A subsample is created with each of these definitions. We compute the dependent variable as the logarithm of the size of the next fund raised by the venture capital firm. If the VC firm does not raise capital subsequent to the IPO, we set the dependent variable equal to zero. If a venture capital firm is the lead investor in more than one IPO in a year, then the observations in the subsamples are not independent and the errors are correlated. To correct for this, we replace such observations with their average value.

[5] Gompers (1996) regards the VC firm that has been on the board of the IPO firm the longest as the lead venture capitalist. Since we do not have board information prior to the IPO, we simply regard the oldest VC as the lead VC. Another alternative would be to use information on all venture capitalists. However, this would induce severe dependence problems in the regressions since the same IPO would appear multiple times in the data.

We use several control variables in the regressions. We include the CRSP value-weighted market return and the total volume of IPOs in that year as controls because Gompers and Lerner (1998) show that these variables are related to venture capital fundraising, at both an aggregate and firm level. Following Gompers (1996), we also include underwriter rank as a control variable and estimate the regressions with calendar and industry fixed effects. We use the two measures of VC reputation discussed above as primary explanatory variables (VC age and the number of previous IPOs conducted by the venture capital firm). We also consider two measures by which the VC firm can signal its reputation. The first, suggested by the arguments in the preceding section, is IPO underpricing. VC firms that need to establish their reputation are more likely to bear the cost of higher underpricing. The second is IPO size, defined as the number of shares multiplied by the offer price. The return earned by the VC firm (and therefore by the limited partners) is a function of the size of the IPO. Therefore, IPO size may in fact be a better signal than underpricing. Since IPO size is highly correlated with underpricing ($\rho = 0.74$), we use these variables in separate regressions.

The grandstanding arguments in the previous section make specific predictions about the interaction between reputation and IPO underpricing (or IPO size). Therefore, we include interaction terms between the two measures of reputation and underpricing and IPO size. Table 5 shows parameter estimates for regressions in which the lead VC firm is defined as the one with the largest investment in the IPO firm, and Table 6 shows estimates for the subsample in which the lead VC firm is the earliest investor in the IPO firm. *P*-values appear in parentheses.

The two measures of reputation, the VC age and the number of previous IPOs by the VC firm, are positive and statistically significant in all specifications and in both subsamples (Tables 5 and 6). This indicates that more-reputable firms are able to raise more capital. A behavioral story in which investors extrapolate recent performance (i.e., taking a portfolio company public) into the future would also predict a positive coefficient on the number of previous IPOs conducted by the VC. However, such a story cannot predict the coefficient on VC age, or the interaction effects with underpricing. First-day returns are also positively related to future capital flows in both subsamples. The average coefficient for models in which the lead VC has the largest (first) stake in the IPO firm is 0.34 (0.10). In contrast, IPO size is statistically significant in only one specification, with a *p*-value of 0.07. We can think of two reasons why underpricing is significant in these regressions but IPO size is not. First, there is a great deal of focus in both the capital markets and the press on the first-day return. Indeed, first-day "pops" (as they are often referred to) are widely reported and followed by retail investors and entrepreneurial firms. IPO size does not receive such lavish attention. Second, for a signal to be credible, it must be costly to the agent (Spence, 1973). Underpricing reflects the cost of the wealth transfer from old shareholders (including the VC firm) to new shareholders. This cost, measured by the first-day return, is very visible. In contrast, the cost associated with suboptimal IPO size is more difficult to ascertain because investors do not have direct measures of optimal IPO size.

Table 5

Fundraising regressions for VC with largest investment in IPO

The sample consists of VCs with the largest stake in the company prior to the IPO. The dependent variable in the regressions below is the logarithm of the next fund raised by the VC subsequent to the IPO. If no money is raised subsequent to the IPO, the dependent variable is set to zero. The CRSP value-weighted return is for the year of the IPO. IPO size is calculated as the number of shares multiplied by the offer price. VC age is measured in years. Industry fixed effects are based on two-digit SIC codes. *P*-values appear in parentheses.

Intercept	−0.8077	−0.3747	1.4238	−1.2209
	(0.02)	(0.79)	(0.00)	(0.41)
CRSP value-weighted return	−0.0014	−0.0014	−0.0013	−0.0015
	(0.15)	(0.15)	(0.16)	(0.13)
Total number of IPOs in the year of the IPO	0.0000	−0.0001	−0.0003	−0.0004
	(0.95)	(0.77)	(0.39)	(0.27)
Underwriter rank	0.0373	0.0192	0.0079	—
	(0.33)	(0.67)	(0.83)	
First-day IPO return	0.1090	—	0.5548	—
	(0.00)		(0.00)	
Logarithm (IPO size)	—	0.0723	—	0.1673
		(0.44)		(0.07)
Logarithm (VC age)	0.3989	0.4649	—	—
	(0.00)	(0.00)		
Logarithm (number of previous IPOs by VC)	—	—	0.8889	2.1585
			(0.00)	(0.00)
VC age * first-day return	−0.2517	—	—	—
	(0.00)			
VC age * IPO size	—	−0.0001	—	—
		(0.09)		
Number of previous IPOs * first-day return	—	—	−0.0854	
			(0.00)	
Number of previous IPOs * IPO size	—	—	—	−0.0068
				(0.41)
Industry fixed effects	Yes	Yes	Yes	Yes
Calendar fixed effects	Yes	Yes	Yes	Yes
Adj-R^2	0.08	0.06	0.11	0.10

The grandstanding argument predicts that less-established VC firms have more to gain from signaling their quality. This implies that the interaction effect between VC age and underpricing, and between the number of previous IPOs done by the VC firm and underpricing, should be negative. In Table 5, both interaction terms are negative and have p-values of 0.00. In Table 6, the interaction terms are also negative and have p-values of 0.05 and 0.03, respectively. We also estimate specifications in which we interact VC age and the number of previous IPOs with IPO size. The coefficients on these interactions terms are not statistically significant. This is not surprising since IPO size itself is not related to future fundraising.

The cross-sectional predictions of the grandstanding hypothesis are supported by the data. However, the grandstanding argument does not predict that underpricing by itself should be positively related to future capital flows – a positive coefficient on

Table 6
Fundraising regressions for VC with earliest investment in IPO
The sample consists of VCs with the earliest stake in the company prior to the IPO. The dependent variable in the regressions below is the logarithm of the next fund raised by the VC subsequent to the IPO. If no money is raised subsequent to the IPO, the dependent variable is set to zero. The CRSP value-weighted return is for the year of the IPO. IPO size is calculated as the number of shares multiplied by the offer price. VC age is measured in years. Industry fixed effects are based on two-digit SIC codes. *P*-values appear in parentheses.

Intercept	1.5985	−0.3338	−2.0669	1.2263
	(0.00)	(0.81)	(0.00)	(0.43)
CRSP value-weighted return	0.0006	0.0003	0.0001	0.0000
	(0.057)	(0.76)	(0.85)	(0.96)
Total number of IPOs in the year of the IPO	0.0007	0.0008	0.0008	0.0009
	(0.07)	(0.07)	(0.03)	(0.04)
Underwriter rank	−0.0211	0.0407	−0.0438	—
	(0.61)	(0.41)	(0.29)	
First-day IPO return	0.1062	—	0.0997	—
	(0.04)		(0.05)	
Logarithm (IPO size)	—	0.1195	—	0.0535
		(0.19)		(0.59)
Logarithm (VC age)	0.3590	0.4168	—	—
	(0.00)	(0.00)		
Logarithm (number of previous IPOs by VC)	—	—	0.7270	0.7049
			(0.00)	(0.05)
VC age * first-day return	−0.0784	—	—	—
	(0.05)			
VC age * IPO size	—	−0.0001	—	—
		(0.12)		
Number of previous IPOs * first-day return	—	—	−0.2715	—
			(0.03)	
Number of previous IPOs * IPO size	—	—	—	0.0062
				(0.94)
Industry fixed effects	Yes	Yes	Yes	Yes
Calendar fixed effects	Yes	Yes	Yes	Yes
Adj-R^2	0.04	0.04	0.08	0.08

first-day returns is somewhat surprising. We speculate that the growth and increase in competition in the venture capital industry in the late 1990s is driving some of this result. Panel A of Table 7 shows the number of existing venture capital firms, the number of net new firms, the total number of firms, and the number of net new venture capital funds raised in each year of the time series. These aggregate data are provided to us by Thomson Venture Economics and generated from the Venture Economics database. On average, 33 new firms entered the industry each year between 1980 and 1996. Between 1997 and 2000, this average rose to 106 firms. This dramatic change in industry profile has two consequences for our results. First, the latter part of our sample is likely to have a larger fraction of new VC firms. Second, if the entry of new firms is associated with an increase in competition, even incumbent

Table 7

Growth in VC firms and subperiod regressions

Panel A shows the number of existing venture capital firms, the number of net new firms, and the total number of firms in each year. It also shows the number of net new venture capital funds raised in each year. These data are courtesy Thompson Financial Corporation. Panels B and C show selected coefficients from fundraising regressions estimated from the 1980–1996 and 1997–2000 subperiods. The regression specifications are identical to those in Tables 5 and 6. Panel B regressions are estimated for VCs with the largest investment in the IPO. Panel C regressions are estimated for VCs with the earliest investment in the IPO. *P*-values appear in parentheses.

Year	Existing firms	Net New firms	Total firms	Net new funds
Panel A: Growth in VC firms				
1980	87	21	109	45
1981	122	37	146	64
1982	153	34	180	69
1983	199	43	223	115
1984	251	50	273	117
1985	289	33	306	91
1986	321	32	338	82
1987	355	37	375	107
1988	368	19	394	82
1989	383	29	423	93
1990	386	15	438	62
1991	368	8	446	43
1992	363	22	468	78
1993	373	28	496	94
1994	386	32	528	103
1995	422	64	592	154
1996	464	57	649	145
1997	540	94	649	222
1998	612	81	743	235
1999	734	129	824	340
2000	840	123	953	386

	1980–1996		1997–2000	
Panel B: Selected coefficients from subperiod fundraising regressions for VCs with largest investment in IPO				
First-day IPO return	0.9076	0.9817	0.0655	0.3770
	(0.22)	(0.07)	(0.02)	(0.05)
Logarithm (VC age)	0.4215	—	0.4002	—
	(0.00)		(0.00)	
Logarithm (number of previous IPOs)	—	1.0167	—	0.6897)
		(0.00)		(0.00)
VC age $*$ first-day return	−0.0284	—	−0.2415	—
	(0.09)		(0.06)	
Number of previous IPOs $*$ first-day return	—	−0.3644	—	−0.2514
		(0.07)		(0.09)

	1980–1996		1997–2000	
Panel C: Selected coefficients from subperiod fundraising regressions for VCs with earliest investment in IPO				
First-day IPO return	1.4847	0.9328	0.0105	0.1391
	(0.06)	(0.13)	(0.04)	(0.04)
Logarithm (VC age)	0.3381	—	0.3189	—

Table 7 (*continued*)

Year	Existing firms	Net New firms	Total firms	Net new funds
	(0.00)		(0.03)	
Logarithm (number of previous IPOs)	—	0.6336	—	0.7750
		(0.00)		(0.00)
VC age * first-day return	−0.2071	—	−0.1148	—
	(0.07)		(0.07)	
Number of previous IPOs * first-day return	—	−0.2096	—	−0.1813
		(0.04)		(0.13)

firms might have to incur some underpricing costs to maintain their reputation. In either case, estimating regressions for these subperiods is likely to be informative.

Panels B and C show selected coefficients from fundraising regressions estimated for the 1980–1996 and 1997–2000 subperiods. (We also estimate these regressions using 1996 as a breakpoint for the two subperiods; the results are similar and are not reported.) The regression specifications are identical to those in Tables 5 and 6 but only the coefficients on first-day returns, VC age, the number of previous IPOs, and interaction effects are shown. Panel B (C) shows results for the subsample in which the lead VC is defined as the largest (earliest) investor in the IPO firm.

The results show that IPO underpricing is positively related to future fundraising in the 1997–2000 subperiod but this relation is much weaker in the earlier subperiod. Two of the four coefficients in the first subperiod are statistically insignificant. In the 1997–2000 subperiod, all four underpricing coefficients are positive and statistically significant. The cross-sectional relation between our two measures of VC reputation and underpricing are evident in both subperiods, suggesting that cross-sectional grandstanding effects are persistent.

4.3. Grandstanding and IPO characteristics

Under the grandstanding hypothesis, venture capital firms that need to establish a reputation are more willing to bring smaller, younger, and perhaps riskier companies to the public market. This should be reflected in the cross-sectional dispersion of IPO characteristics with respect to various measures of VC firm reputation.

We estimate regressions of our proxies for reputation on IPO characteristics in Table 8. Again, the regressions are estimated separately for the two lead-VC subsamples. As independent variables, we use total revenue and age for the IPO firm, and net proceeds and underwriter rank of the IPO. We do not include book value or total assets in the regressions because they are highly correlated with revenue. Other IPO characteristics such as gross spread display very little variation across IPOs, and are also excluded from the specification.

The regressions show that both VC age and the number of prior IPOs conducted by the VC firm are positively related to total revenues of the IPO firm. In addition, VC age is positively related to the age of the IPO firm, implying that younger venture capitalists take younger companies public. Consistent with Gompers (1996), younger

Table 8
Regressions of VC age and number of previous IPOs on firm and IPO characteristics
The table shows regressions of two measures of reputation on IPO characteristics. The regressions are estimated for two subsamples. The first subsample consists of IPOs in which the lead VC is one that had the largest stake in the firm prior to the IPO. The second subsample is that of IPOs in which the lead VC was the one with the first investment in the pre-IPO firm. The dependent variables are the logarithm of the age of the VC at the time of the IPO and the logarithm of the number of previous IPOs conducted by the VC. Revenues are measured immediately after the IPO. Age is measured in years at the time of the IPO. *P*-values appear in parentheses.

	VC with first investment in IPO firm		VC with largest stake in IPO firm	
Dependent variable	VC age	Number of previous IPOs	VC age	Number of previous IPOs
Constant	2.0700	0.3060	2.0735	−0.0410
	(0.00)	(0.27)	(0.00)	(0.89)
Log (revenue)	0.0469	0.0576	0.0030	0.0245
	(0.05)	(0.00)	(0.03)	(0.22)
Log (age at IPO)	0.1626	0.0564	0.1820	0.0168
	(0.00)	(0.32)	(0.00)	(0.74)
Log (underwriter rank)	−0.1524	0.1219	0.1135	0.2692
	(0.40)	(0.38)	(0.51)	(0.07)
Log (net proceeds)	−0.0105	−0.0287	0.0273	0.0570
	(0.88)	(0.65)	(0.67)	(0.30)
Adj-R^2	0.02	0.02	0.02	0.02
N	480	484	544	545

VC firms and those with less experience at taking companies public take smaller and younger companies public.

5. Robustness issues and alternative explanations

The evidence thus far is consistent with the idea that underpricing is related to grandstanding by venture capital firms. This appears to be reflected in the costs they are willing to bear as well as the cross-sectional distribution of the types of firms that engage in this activity. In this section, we consider issues that could affect our inferences and examine other potential explanations for our results.

5.1. *Issues with the dependent variable*

There are several possible sources of error in the specification of the dependent variable in the regressions in Tables 5 and 6. We have followed Gompers (1996) in defining the dependent variable as the logarithm of the size of the next fund raised by the VC firm. For IPOs in the last few years of our sample, however, this could present a problem. Consider, for example, a VC firm that takes a firm public in 2000. Our fundraising data from Venture Economics end in 2001, one year after the end of the IPO sample. Since VC firms raise new venture capital funds with overlapping lives, it could be that a venture capital firm that took a portfolio company public in

2000 raises funds in 2002 or even later. This would not be visible in our sample and the dependent variable would be coded zero because the VC firm did not raise subsequent funds in our sample period.

There are several possible ways to deal with this horizon problem. We could restrict the sample to IPOs ending in some earlier year, say 1995. This would allow sufficient time for fundraising to "catch up" with IPOs. This solution, however, eliminates a very important period of IPO and venture capital activity (1995–2000). Another possibility is to redefine the dependent variable as the amount of funds raised in the year subsequent to the IPO. The advantage of this definition is that it treats all VC firms equally across the time series. We estimate the regressions in Tables 5 and 6 with this definition of the dependent variable using Tobit models because of truncation. We do not report these regressions but our basic results (the positive coefficient on underpricing and the interaction effects) remain qualitatively unchanged.

A second issue with the dependent variable is that it might miss an important element of grandstanding, namely time. Specifically, the next fund raised by a VC firm could be two years after an IPO or ten years after an IPO. These two observations are given the same weight in the regressions. To determine if this makes a difference to our results, we reestimate the regressions in Tables 5 and 6 but weight the observations by the inverse of one plus the number of years till the next fund. Again, our principal results remain qualitatively unchanged.

5.2. Independent variables and specifications issues

In addition to VC age and the number of prior IPOs, we consider another measure of reputation, namely VC size. However, because lagged capital flows determine VC size, regressions with VC size as an independent variable could be misspecified. At a minimum, endogeneity issues could cloud inferences. Therefore, we elect not to use VC size in the regressions.

The regressions in Tables 5 and 6 never include first-day returns and IPO size in the same model because of the high correlation between these two variables ($\rho = 0.74$). However, it would be useful to know which effect dominates. To determine this, we orthogonalize each variable with respect to the other, and include the orthogonalized transformations in the regressions. When the lead VC is the largest investor in the IPO, the coefficient on orthogonalized first-day return is 0.3614 (t-statistic = 5.4) and the coefficient on the orthogonalized IPO size is –0.0674 (t-statistic $= -0.84$). When the lead VC is the earliest investor in the IPO, the corresponding coefficients are 0.1357 (t-statistic = 2.94) and 0.0058 (t-statistic = 0.94), respectively. Thus, consistent with the results in Tables 5 and 6, underpricing influences future fundraising but IPO size does not.

5.3. Alternative explanations

We consider other explanations for our results. As we discuss in the introduction, it is possible that underwriters preferentially allocate shares of other underpriced

IPOs to venture capital firms in exchange for greater underpricing in the VC firm's own portfolio firm. Negative publicity, indictments, and regulatory investigations into IPO allocations in the internet bubble period are certainly suggestive of this explanation. However, our results are drawn from a long time series. We doubt that such an explanation can account for results in other sample periods.

Another possibility is the "recycling hypothesis" described by Gompers (1996). This hypothesis relies on the idea that investors in venture capital firms reinvest profits from earlier venture investments into new VC funds (i.e., recycle their profits). The sooner VC firms return cash to their institutional investors, the sooner they receive additional capital. This suggests that taking a portfolio company public leads to future inflows of capital but does not explain why underpricing should be related to future capital flows. Moreover, it does not explain the cross-sectional dispersion in capital flows or the interaction effects with underpricing.

Finally, Loughran and Ritter (2002b) use prospect theory to explain why issuers are willing to leave money on the table. They argue that issuers ignore the wealth loss from underpricing because they sum this wealth loss with the wealth gain from the IPO itself. Since the net effect is a wealth gain, investors simply ignore the loss due to underpricing. If this is true, then the positive relation between underpricing and future capital flows could simply be an IPO effect, rather than an underpricing effect.

Disentangling the incremental impact of underpricing from the effect of the IPO is a difficult task because underpricing is only observed at the time of the IPO. Therefore, any attempt to distinguish the two effects requires that the sample contain VC firms that do not take a company public, as well as VC firms that lead IPOs. We compile a sample of all venture capital firms that are in existence in a given year. As described in Section 2, our data-gathering procedures account for name changes, consolidations and other such events by manually reading records from annual issues of *Pratt's Guide to Venture Capital Sources*. We then merge this sample with our database of venture capital firms that took a company public in each given year. The consolidated sample consists of a panel dataset that includes venture capital firms that were involved in an IPO and others that were not. The database of venture capital firms that took a company public in any given year is somewhat different from the subsamples used in the regressions in Tables 5 and 6. This is because, for this test, we need to know if a particular venture capital firm held *any* equity stake in the IPO firm (not just the largest stake).

Even with this sample, it is inappropriate to estimate fundraising regressions with an IPO indicator (equal to one if the VC firm conducted an IPO, zero otherwise) and first-day returns in the same model. This is because there is a causal relation between the two regressors – underpricing can only be observed if the company is taken public. The solution to this observability problem is to estimate the underpricing effect via Heckman's (1979) two-stage procedure. The first stage is a probit regression that estimates the probability that underpricing is not observed (or, equivalently, that a sample VC firm takes a portfolio company public). In the second stage, the dependent variable is the logarithm of the size of the next fund. The coefficient on underpricing in the second stage is adjusted for the fact that underpricing is not always observed. The difficulty in such procedures is always in

Table 9
Heckman Regressions
The sample consists of all venture firms in existence in each year from 1980 to 2000. Venture firms that took a portfolio company public, as well as those that did not, are included in the sample. Two-stage Heckman (1979) regressions are estimated to account for the fact that underpricing is only observed when a portfolio company is taken public. The dependent variable in the first-stage regression is the probability that a VC firm takes a portfolio company public. The dependent variable in the second-stage regression is the logarithm of size of the next fund. VC age is measured in years. The number of portfolio companies is the total number of companies in which the venture firm has investments in that calendar year. Panel estimates are based on the entire cross-section and time series of venture capital firms. The last two columns show average coefficients from similar year-by-year regressions, with p-values based on time-series standard errors. P-values appear in parentheses.

	Panel estimates		Year-by-year regression estimates	
Panel A: Stage I regressions				
Constant	−1.1839	−1.6100	−1.3683	−1.9854
	(0.00)	(0.00)	(0.00)	(0.00)
Logarithm (VC age)	0.3358	0.2273	0.3035	0.2513
	(0.00)	(0.00)	(0.00)	(0.00)
Number of portfolio companies	0.0032	—	0.0267	—
	(0.00)		(0.00)	
Logarithm (VC size)	—	0.2168	—	0.2415
		(0.00)		(0.00)
Calendar indicators	Yes	Yes	No	No
Λ	−0.2047	−0.5383	−0.6290	−0.7703
	(0.01)	(0.00)	(0.00)	(0.00)
Pseudo R^2	0.10	0.12		—
Panel B: Stage II fundraising regressions				
Constant	0.5046	0.9240	1.0246	1.2915
	(0.00)	(0.00)	(0.00)	(0.00)
First-day return	0.2557	0.3417	0.5834	1.1727
	(0.00)	(0.00)	(0.00)	(0.00)

identifying appropriate regressors for the first-stage regression. We use VC age, the number of companies in the venture firm's portfolio in that year, VC size, and calendar year indicator variables as instruments in the first-stage regression. We expect older venture capital firms and those with more companies in their portfolio to be more likely to conduct an IPO. Since data on VC size is sparse, it reduces the effective sample size. Therefore, we estimate separate models with VC size and the number of companies in the venture firm's portfolio. We estimate these regressions in two ways. First, we estimate models on the entire panel. Second, since the error terms in the panel are likely to be correlated, we estimate Fama-MacBeth regressions and report average coefficients.

Panel A of Table 9 shows the results of the first-stage regressions. The panel estimates, which appear in the first two columns, show that VC age, the number of companies in the VC firm's portfolio, and VC size are positively related to the probability that the venture firm will take a portfolio company public. Average coefficients from similar annual regressions (with p-values based on time-series standard errors) are similar in size and significance. The pseudo-R^2s of the panel regressions are 0.10 and 0.12, indicating that the regressions have reasonable explanatory power. In the second stage, the coefficients on first-day returns are positive and statistically significant in all models. This suggests that underpricing has an impact on future fundraising over and beyond the fact that it is only observed when a firm is taken public.

6. Conclusion

We investigate the role of venture capitalists in the underpricing of IPOs between 1980 and 2000. We argue that the provision and receipt of venture financing represents an endogenous choice on the part of the venture capitalist and the entrepreneur. We use instruments correlated with this endogenous choice to control for selection bias and compare the underpricing of VC backed and non-VC backed IPOs. Our results show that VC backed IPOs exhibit greater underpricing than non-VC backed IPOs. The return differential ranges from 5.0% to 10.3% over the entire sample period. During the internet bubble period of 1999–2000, the differential is significantly larger.

Larger underpricing represents a real cost to venture capitalists because there is a wealth transfer from them (and from other pre-IPO shareholders) to new shareholders. We explore a variant of the grandstanding hypothesis proposed by Gompers (1996) as an explanation for this result. We estimate capital flow regressions with measures of reputation, underpricing, and interaction effects as explanatory variables. These regressions detect a positive relation between reputation proxies and future fundraising, and between first-day returns and future fundraising. Interaction effects between reputation and underpricing are negative, suggesting that low-reputation firms benefit more from grandstanding. Overall, the data are consistent with the idea that grandstanding provides a compensating benefit to the cost associated with incremental underpricing of VC backed IPOs.

References

Ackerberg, D., Botticini, M., 2002. Endogenous matching and the empirical determinants of contract form. Journal of Political Economy 110, 564–591.

Barry, C., Muscarella, C., Peavy, J., Vetsuypens, M., 1990. The role of venture capital in the creation of public companies: evidence from the going-public process. Journal of Financial Economics 27, 447–472.

Beatty, R., Welch, I., 1996. Issue expenses and legal liability in initial public offerings. Journal of Law and Economics 39, 545–602.

Black, B., Gilson, R., 1998. Venture capita and the structure of capital markets: banks versus stock markets. Journal of Financial Economics 47, 243–277.

Bradley, D., Jordan, B., 2002. Partial adjustment to public information and IPO underpricing. Journal of Financial and Quantitative Analysis 37, 595–616.

Carter, R., Manaster, S., 1990. Initial public offerings and underwriter reputation. Journal of Finance 1045–1067.
Carter, R., Dark, F., Singh, A., 1998. Underwriter reputation, initial returns and the long run performance of IPO stocks. Journal of Finance 53, 295–311.
Chen, H., Ritter, J., 2000. The seven percent solution. Journal of Finance 55, 1105–1131.
Dehejia, R., Wahba, S., 1999. Causal effects in non-experimental studies: evaluating the evaluation of training programs. Journal of the American Statistical Association 94, 1053–1062.
Gompers, P., 1995. Optimal investment, monitoring and the staging of venture capital. Journal of Finance 50, 1461–1489.
Gompers, P., 1996. Grandstanding in the venture capital industry. Journal of Financial Economics 42, 133–156.
Gompers, P., Lerner, J., 1996. The use of covenants: an empirical analysis of venture partnership agreements. Journal of Law and Economics 39, 463–498.
Gompers, P., Lerner, J., 1997. Venture capital and the creation of public companies: do venture capitalists really bring more than money? Journal of Private Equity 15–32.
Gompers, P., Lerner, J., 1998. What drives venture capital fundraising. Brookings Papers on Economic Activity – Microeconomics 149-192.
Gompers, P., Lerner, J., 2000. Money chasing deals? the impact of fund inflows on private equity valuations. Journal of Financial Economics 55, 281–325.
Gompers, P., Lerner, J., 2001. The venture capital revolution. Journal of Economic Perspectives 15, 145–168.
Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.
Heckman, J., Ichimura, H., Todd, P., 1997. Matching as an econometric evaluation estimator: evidence from evaluating a job training program. Review of Economic Studies 64, 605–654.
Heckman, J., Ichimura, H., Todd, P., 1998. Matching as an econometric evaluation estimator. Review of Economic Studies 65, 261–294.
Hellman, T., 1998. The allocation of control rights in venture capital contracts. Rand Journal of Economics 29, 57–76.
Hellman, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: empirical evidence. Journal of Finance 57, 169–197.
Ibbotson, R., Jaffe, J., 1975. ‘‘Hot issue’’ markets. Journal of Finance 30, 1027–1042.
Kaplan, S., Stromberg, P., 2001. Financial contracting theory meets the real world: an empirical analysis of venture capital contracts. Working paper, University of Chicago.
Kaplan, S., Stromberg, P., 2002, Characteristics, contracts and actions: evidence from venture capital analyses. Working paper, University of Chicago.
LaLonde, R., 1986. Evaluating the econometric evaluations of training programs with experimental data. American Economic Review 76, 604–620.
Lerner, J., 1994. Venture capitalists and the decision to go public. Journal of Financial Economics 35, 293–316.
Lerner, J., 1995. Venture capitalists and the oversight of public firms. Journal of Finance 50, 301–318.
Ljungqvist, A., Wilhelm, W., 2003. IPO pricing in the dot-com bubble. Journal of Finance 58, 723–752.
Loughran, T., Ritter, J., 2002a. Why has IPO underpricing increased over time? Working paper, University of Florida.
Loughran, T., Ritter, J., 2002b. Why don't issuers get upset about leaving money on the table in IPOs? Review of Financial Studies 15, 413–443.
Lowry, M., Schwert, G.W., 2002. Ipo market cycles: bubbles or sequential learning. Journal of Finance 57, 1171–1200.
Madalla, G.S., 1983. Limited-dependent and qualitative variables in econometrics. Econometric Society Monographs No. 3. Cambridge University Press, Cambridge.
Madhavan, A., Cheng, M., 1997. In search of liquidity: block trades in the upstairs and downstairs markets. Review of Financial Studies 10, 175–203.
Megginson, W., 2004. Towards a global model of venture capital? Journal of Applied Corporate Finance, forthcoming.

Megginson, W., Weiss, K., 1991. Venture capitalist certification in initial public offerings. Journal of Finance 46, 879–903.

Ritter, J., 1984. The "hot issue" market of 1980. Journal of Business 57, 215–240.

Ritter, J., Welch, I., 2002. A review of IPO activity, pricing and allocations. Journal of Finance 57, 1795–1828.

Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.

Rubin, D., 1974. Estimating causal effects of treatments in randomized and non-randomized studies. Journal Educational Psychology 66, 688–701.

Rubin, D., 1977. Assignment to a treatment group on the basis of a covariate. Journal of Educational Statistics 2, 1–26.

Sahlman, W., 1990. The structure and governance of venture-capital organizations. Journal of Financial Economics 27, 473–521.

Spence, M., 1973. Job market signaling. Quarterly Journal of Economics 87, 355–379.