

# IPO Price Formation and Board Gender Diversity

Finance Working Paper N° 756/2021 March 2023 P. Raghavendra Rau University of Cambridge

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# Abstract

We study the relation between board gender diversity and initial public offering (IPO) price formation. We find that IPOs experience significantly greater underpricing when the firm's board has at least one female director on it, relative to when no women sit on the board. The underpricing effect is not attributable to differences in profitability, growth opportunities, CSR scores, CEO gender, director experience, or other firm, director, or underwriter characteristics. Instead, the underpricing effect appears to be driven by increased non-pecuniary institutional investor demand for board gender diversity over the most recent decade. Board gender diversity does not impact the initial file price of the IPO or the offer price adjustment, suggesting that institutional investors who are not invited to participate in the IPO book-building process are likely driving the underpricing effect. We find that the underpricing effect is attenuated for IPOs with underwriters that have relatively greater network centrality.

Keywords: Initial Public Offerings, Information Processing, Going Public Process, Gender Diversity, Underpricing, Investment Banks, Corporate Governance, Network Centrality

JEL Classifications: G24, G30, J16

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# IPO Price Formation and Board Gender Diversity

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# ABSTRACT

We study the relation between board gender diversity and initial public offering (IPO) price formation. We find that IPOs experience significantly greater underpricing when the firm's board has at least one female director on it, relative to when no women sit on the board. The underpricing effect is not attributable to differences in profitability, growth opportunities, CSR scores, CEO gender, director experience, or other firm, director, or underwriter characteristics. Instead, the underpricing effect appears to be driven by increased non-pecuniary institutional investor demand for board gender diversity over the most recent decade. Board gender diversity does not impact the initial file price of the IPO or the offer price adjustment, suggesting that institutional investors who are not invited to participate in the IPO book-building process are likely driving the underpricing effect. We find that the underpricing effect is attenuated for IPOs with underwriters that have relatively greater network centrality.

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#### 1. Introduction

In recent years, investors, regulators, and practitioners worldwide have demanded an increase in female representation on corporate boards (Srinidhi et al., 2011; Moody's, 2019; Gormley et al., 2020). In particular, several of the largest institutional investors have publicly communicated their preference for gender-diverse board firms. Between 2017 and 2018, for example, BlackRock, State Street, and Vanguard each launched campaigns to increase gender diversity on corporate boards, which included making portfolio holding decisions based on board gender diversity metrics (Gormley et al., 2020). This preference for board gender diversity is a relatively recent phenomenon, and little is known about how this preference impacts firm valuations.<sup>1</sup> In this study, we examine how board gender diversity affects firm value during the initial public offering (IPO) process, when outside investors are explicitly asked to provide information about their valuations of the firm.

The IPO process provides a unique setting to study the impact that investor preferences have on firm valuations. When a company decides to go public, an initial price range is set for the company's stock, and then the underwriters of the IPO begin the book-building process (Willenborg et al., 2015). During the book-building process, the underwriters elicit information from potential investors about their interest in the firm's stock, and this information is used to set the final offer price of the IPO and allocate shares to the initial investors (Blankespoor et al., 2017). On the first day a stock is publicly traded, it is common for the price to rise substantially (Ritter and Welch, 2002), which is referred to as underpricing. As a company's fundamental value is unlikely to have changed over the course of the first trading day, underpricing suggests that not all information about investors' preferences for the stock was incorporated into the offer price.

Investor preferences for board gender diversity could impact IPO price formation, and consequently underpricing, for multiple reasons. Benveniste and Spindt (1989) posit that investors who are optimistic about the company's value will not want to disclose this information to the underwriter during the book-building process because they do not want the offer price to increase. In

<sup>&</sup>lt;sup>1</sup>The empirical relation between board gender diversity and corporate performance continues to be a hotly debated issue (Eckbo et al., 2021).

order for these investors to truthfully reveal their valuations of the firm, underwriters must reward them through a favorable share allocation and by only partially adjusting the offer price upward. Although the interpretation of Benveniste and Spindt (1989) is that investors' valuations are driven by their private information about the expected cash flows of the firm, their valuations could also be impacted if they assign a larger or smaller cost of capital to certain firms (Fama and French, 2007). For instance, Fabozzi et al. (2008) show that investors demand a higher return from "sin stocks," whereas Renneboog et al. (2007) suggest that investors in "ethical funds" trade off expected returns for the non-pecuniary benefits they enjoy from owning more ethical stocks. Similarly, investors may believe that female representation on corporate boards is important for reasons beyond firm-specific value creation, such as the notion that female representation among leaders is important for future generations to believe they can succeed in a certain profession (Porter and Serra, 2020). Regardless of whether investor demand for board gender diversity is driven by future cash flow expectations or by non-pecuniary motivations, if their preferences are not fully incorporated into the offer price, gender-diverse board IPOs will realize greater underpricing than will non-diverse board IPOs. This is what we find in the data.

In our sample of over 1,100 U.S. IPOs from 2000–2018, we find that board gender diversity is positively related to underpricing. This effect is economically meaningful and statistically significant across the entire sample period, suggesting that gender-diverse board IPOs realize underpricing that is 4.9–5.7 percentage points greater than that realized by non-diverse board IPOs. This equates to gender-diverse board IPOs incurring approximately \$11 million more in unrealized proceeds. These results are robust to controlling for a host of possible confounding factors that may jointly affect board gender diversity and underpricing, such as CEO gender, industry classification, firm age, VC involvement, and firm size. In addition, the underpricing effect is not attributable to differences in profitability, growth opportunities, CSR scores, director experience, or other aspects of board diversity, such as ethnic/racial and age diversity. Furthermore, the positive relation between board gender diversity and IPO underpricing is robust to the use of entropy balancing, which is a generalized form of propensity score matching. If the underpricing effect is driven by investor demand for gender-diverse board firms, we would only expect to see the underpricing effect emerge in years when investors have preferences for board gender diversity. We find that gender-diverse and non-diverse board IPOs have very similar levels of underpricing in the 2000–2009 period, but then the underpricing of gender-diverse board IPOs jumps upward in the beginning of the 2010s and remains at a higher level for the remainder of the decade. When we re-estimate our main tests splitting the data across decades, we find that nearly all of the gender diversity underpricing effect is driven by IPOs in the 2010–2018 period. We conjecture that one of the events that may have caused a newfound demand for board gender diversity—and, subsequently, increased underpricing among gender-diverse board IPOs—was the SEC's 2010 requirement that public companies disclose the role that diversity considerations play when they select directors.<sup>2</sup>

We expect that the increased demand for the shares of gender-diverse board IPOs is driven by institutional investors, as several major investors have publicized this preference for diversity (Gormley et al., 2020), and not by retail investors, as prior research suggests that these investors are relatively indifferent to corporate social and governance concerns (Moss et al., 2020). In order to precisely identify the effect that institutional investors have on the underpricing of gender-diverse board IPOs, we use data from TAQ to differentiate between institutional and retail investor trading behavior on the IPO firm's first trading day. We find that the greater underpricing of genderdiverse board IPOs in the 2010–2018 period is largely caused by the large block trades made by institutional investors. As further evidence of the heightened demand of institutional investors for gender-diverse board firms, we find that the institutional ownership of gender-diverse board IPOs is significantly greater in the 2010–2018 period than it was in the 2000–2009 period. This further suggests that institutional investor demand for board gender diversity has increased over time, contributing to the observed underpricing effect.

<sup>&</sup>lt;sup>2</sup>Several large pension funds, including CalPERS and CalSTRS, wrote letters in support of this regulation (see Footnote 116 in https://www.sec.gov/rules/final/2009/33-9089.pdf). After this mandate went into effect, there were several prominent IPOs that did not initially include women on their board—specifically, Facebook (2012) and Twitter (2013)—creating a good deal of controversy for the firms (see https://www.theguardian.com/commentisfree/2013/oct/11/twitter-ipo-women-board).

If investors who are invited to the book-building process disclose their preferences for board gender diversity, either explicitly or by oversubscribing to the IPO shares, underwriters should adjust the offer price upwards to account for this excess demand. Prior research has found that factors like operating performance and internet classification affect early-stage IPO pricing, such as the revision from the initial file price to the final offer price (Bartov et al., 2002; Willenborg et al., 2015; Blankespoor et al., 2017). We do not find any evidence that this occurs in our setting, as board gender diversity does not impact price formation at any of the earlier stages of the IPO process. This suggests that the investors invited to the book-building process do not express a preference for additional IPO shares of gender-diverse board IPOs, so the underpricing effect is most likely driven by institutional investors who were not involved in the book-building process, as their preferences for board gender diversity would not have been factored into the offer price of the IPO.

A remaining question is whether underwriters eventually learn to incorporate this excess demand for board gender diversity into the IPO price formation process. This could occur if underwriters increase their supply of institutional investor clients over time—especially if diversityfocused investors are added to the supply—which would help underwriters more fully incorporate preferences for board gender diversity into final offer prices. In line with the information extraction hypothesis of Bajo et al. (2016), we hypothesize that underwriters that are more connected with other investment banks should be better suited to efficiently and accurately incorporate preferences for board gender diversity into IPO pricing. We test this hypothesis by estimating the effect of underwriter network centrality on the underpricing of gender-diverse board IPOs. We find evidence that well-connected underwriters appear better able to price the rising demand for gender-diverse board firms. Their ability to mitigate the underpricing effect is especially strong in the last years of the sample period, when BlackRock, State Street, and Vanguard launched their diversity campaigns wherein they explicitly publicized their preferences for board gender diversity. Even after these campaigns, however, gender-diverse board IPOs with *poorly* connected underwriters continue to realize significantly greater underpricing, indicating that these underwriters are less able to accurately incorporate information about diversity preferences into IPO prices.

As previously mentioned, institutional investors may have preferences for board gender diversity for either cash flow-relevant reasons or non-pecuniary reasons. For example, among cash-flow relevant reasons, institutional investors may believe that gender-diverse board firms are more profitable than non-diverse board firms. So, the high demand for gender-diverse board IPOs from institutional investors could be due to their belief that these firms will outperform in the long-run after the IPO. However, we find that after the stock is publicly traded, board gender diversity at the time of the IPO is uncorrelated with the subsequent accounting performance of the firms, measured by industry- and size-adjusted return on assets. In addition, we find that board gender diversity at the time of IPO is unrelated to instances of future negative corporate events, such as accounting restatements and lawsuits. Alternatively, institutional investors may prefer gender-diverse board firms for non-pecuniary reasons, which could lead them to pay higher prices for the stock of these firms or, equivalently, lead them to require lower rates of return when investing in these firms. In line with this explanation, Bauer et al. (2019) show that two-thirds of the surveyed members of a pension fund were willing to sacrifice yield if it expanded the fund's engagement with companies practicing sustainable development. Thus, our evidence is consistent with the notion that institutional investors' preferences for board gender diversity increases their willingness to bid up the price of the shares on the first day of trading, an effect equivalent to the underwriters overestimating the firm's cost of capital during the IPO process (Leone et al., 2007).

Finally, we find no evidence that board gender diversity is a form of window-dressing used by firms to appeal to external pressures. Other research suggests that IPO firms, especially those with less experienced management, will hire investor relations consultants to create positive hype for the firm before the IPO date, leading to increased underpricing (Chahine et al., 2020). We find that both male and female directors typically have served on the board for over three years at the time of the IPO, and 90% of the gender-diverse board IPOs remain diverse two years after going public,

so it is very unlikely that board gender diversity is being used as a hype strategy. Rejecting these alternative stories bolsters our conclusion that the gender diversity underpricing effect is driven by the relatively recent demands of institutional investors for gender-diverse board firms.

Our findings contribute to multiple strands of literature in accounting and finance on IPO pricing. Prior work has considered the impact of operating performance, perceptions of management, and earnings quality on the pricing of IPOs (Boulton et al., 2011; Willenborg et al., 2015; Blankespoor et al., 2017), and others have focused on the effects of regulations and legal mandates on IPO performance (Barth et al., 2017; Dambra et al., 2018; Byard et al., 2021). We contribute to this literature by focusing on the increasingly important topic of female representation on corporate boards, finding robust evidence that board gender diversity impacts IPO underpricing. Other research has examined the relation between board diversity and IPO performance in international markets (Handa and Singh, 2015; Eriksen and Särnmo Åberg, 2019; Teti and Montefusco, 2021), but none document a significant effect. This suggests either that investors in these markets do not place a premium on gender diversity or, if they do, underwriters efficiently incorporate the premium into the IPO's offer price. Reutzel and Belsito (2015) use data on U.S. IPOs from 1997 to 2007 and find evidence of decreased underpricing when at least one female is on the board of directors. They show that this negative effect weakens after the Sarbanes-Oxley Act, which aligns with our finding of an insignificant relation between board gender diversity and underpricing in the 2000-2009 period, but the timing of their sample prevents them from uncovering the positive underpricing effect in the 2010–2018 period that we document. Thus et al. (2016) examine a sample of U.S. IPOs that subsequently conduct seasoned equity offerings (SEOs) within two years after going public. However, their sample ends in 2013 and conditions on expost information that is not available at the IPO date (whether the firm will conduct a SEO), so they are not able to identify the effect of board gender diversity on IPO underpricing in the recent decade. So, while board gender diversity's effect on IPO underpricing has been studied previously, we are the first to document a significant, positive relation between female board representation and underpricing.

A second contribution of our paper is our discussion of how institutional investors' preferences for board gender diversity impact IPO underpricing and firm value. Whereas traditional models of IPO underpricing focus on private information about future cash flows (Benveniste and Spindt, 1989), we are among the first to suggest that non-pecuniary preferences that are potentially unrelated to future profitability can also impact underpricing. While many studies have attempted to establish a link between board gender diversity and profitability, our results are consistent with an alternative driver of firm valuations: board gender diversity increases the willingness of investors to pay higher prices for the shares of the company, an effect tantamount to lowering the firm's cost of capital at the time of the offering. In addition, we build upon Bajo et al. (2016) by providing evidence that underwriter network centrality can help investment banks accurately and efficiently price soft information, such as investor preferences for board gender diversity.

Our findings also connect more broadly to the literature on the relation between board composition and firm value. Over the past decade, institutional investors and firms have placed increased emphasis on stakeholder value maximization, diversity, and other CSR-related topics (Graham, 2022). We show in this paper that one such factor, board gender diversity, matters in corporate financing because large institutional investors, and perhaps others, believe it is important. While it remains unclear as to whether gender-diverse boards are actually more effective at increasing firm cash flows, it is clear that the premium placed on diversity by some investors, especially institutional investors, has the potential to lower the cost of capital of gender-diverse board firms. Our IPO setting allows us to directly compare differences in the valuations of stocks due to diversity. By showing that this difference is unrelated to profitability or other characteristics associated with cash flows, we can make a strong case for the argument that board gender diversity lowers the cost of capital, at least at the time the firm goes public.

This paper is organized as follows. In Section 2, we provide a brief discussion of the theories of IPO underpricing and an overview of the related literature on board gender diversity. Section 3 describes our data. In Section 4, we estimate the relation between gender diversity and IPO

underpricing, and we discuss the role of institutional investor demand in driving the effect. In Section 5, we investigate the other possible explanations for the underpricing effect. Section 6 concludes.

#### 2. Motivation and Prior Literature

In order to perform an initial public offering, an issuing company first selects an investment bank to be its lead underwriter (also known as the lead bookrunner) and manage the IPO. The firm must file a registration statement (S-1) with the SEC, in which it describes its business, management, performance, expected growth opportunities, and other characteristics that are of interest to potential investors. Issuing firms will also disclose an initial price range in their S-1 filing, though it has become more common in recent years for the file price range to be set a month or so after the S-1 is filed (Lowry et al., 2020). Once the details in the S-1 are verified by the SEC, the offering becomes effective and the book-building process begins. During the book-building process, the underwriter of the IPO attempts to drum up interest among its institutional investor clients and, at the same time, gather information from them regarding their preferences for the firm's stock. The underwriter uses this information to form the IPO's offer price and determine the share allocation among the investors.

Once shares are allocated to the initial book of investors, trading begins, at which time the general public is able to purchase shares of stock. On this first day of trading, the stock price of IPO firms tends to increase, leading to an end-of-day closing price that often substantially exceeds the offer price. This is called underpricing, a name which suggests the firm's shares were underpriced, as the share price did not accurately reflect that actual demand that investors had for the stock. As a result, the pre-IPO owners of the firm typically end up missing out on millions of dollars in unrealized proceeds.<sup>3</sup> Researchers have documented large and varying levels of underpricing

<sup>&</sup>lt;sup>3</sup>When considering the unrealized proceeds that pre-IPO owners do not collect due to underpricing, it is important to remember that investment banks take each firm public only once, whereas they must interact repeatedly with their institutional investor clients. As such, the goal of the investment bank is not to maximize the value of the issuer, but instead to keep their pool of institutional investors satisfied and willing to continue to invest in future IPOs. Of course, investment banks must also perform well enough on behalf of the issuing firm that they do not incur a loss in reputation that prevents them from underwriting future IPOs.

across time, from over 20% in the 1960s to 40% in the early 2000s (Ibbotson, 1975; Ritter and Welch, 2002), and a host of theoretical and empirical work has been conducted in an attempt to explain this underpricing puzzle.

Ljungqvist (2007) reviews the four main theories that researchers have proposed to explain IPO underpricing: (1) asymmetric information theories, wherein one party of the IPO has information that the others do not possess; (2) institutional theories, which emphasize litigation, price stabilizing, and taxation; (3) control theories, which argue that underpricing is used to augment the ownership structure so as to prevent outsider intervention; and (4) behavioral theories, where investors' irrationality puts upward pressure on the price of the stock over and above its true value. Ljungqvist (2007) writes, "the empirical evidence supports the view that information frictions have a first-order effect on underpricing." One of the most widely cited theories that connects frictions from asymmetric information to underpricing comes from Benveniste and Spindt (1989). They propose that investors who are optimistic about the company's value will not want to disclose this information during the book-building process because doing so will cause the underwriters to increase the offer price. As such, underwriters must incentivize investors to reveal information about their true valuations of the firm by providing the investors with a favorable share allocation and by only partially increasing the offer price. Hanley (1993) find evidence consistent with this partial adjustment phenomenon, and more recent research has found that this effect is strongest among issuers with high operating performance (Willenborg et al., 2015). Underpricing could also occur if underwriters set IPO prices by using "comparable" companies on the basis of cash flows and beta but not on the basis of soft information like preferences for gender diversity. In addition, underpricing may be caused by the demand of investors who are not invited to the book-building process, as their preferences are not factored into the offer price of the IPO.

Why might investors have a preference for owning the stock of firms with greater levels of board gender diversity? First, some research suggests that female director representation leads to increased firm value via better decision-making and increased future cash flows. Kim and Starks (2016) show that female directors contribute unique skills that their male counterparts do not possess, increasing board heterogeneity, and potentially improving corporate investment decisions. Tate and Yang (2015) find evidence that female leadership attenuates gender pay-gaps among rank-and-file employees, which could improve worker satisfaction and productivity, and Griffin et al. (2021) show that board gender diversity is associated with greater corporate innovation. In addition, Srinidhi et al. (2011) find a positive relation between female director representation and earnings quality, which would reduce the likelihood of earnings restatements. The findings of studies performed by consulting firms and asset managers also suggest that gender diversity has a positive economic impact on firm performance (Wagner, 2011; Credit Suisse, 2014; Hunt, 2015; Eastman, 2016; Leadership, 2019; Moody's, 2019; FCLT, 2019; McKinsey, 2020). In contrast, a growing academic literature estimates a negative relation between board gender diversity and firm performance and value (Adams and Ferreira, 2009; Evgeniou and Vermaelen, 2017; Solal and Snellman, 2019). Similarly, Ahern and Dittmar (2012) claim that the Norwegian board gender quota caused a significant drop in short- and long-term firm value among firms that had to increase their board gender diversity, and Matsa and Miller (2013) show that affected firms increased their relative labor costs, reducing short-term profits. Eckbo et al. (2021), on the other hand, argue that the valuation effect of Norway's mandatory quota law was insignificant, and they attribute the findings of prior research to measurement errors.<sup>4</sup> If, however, investors *believe* that board gender diversity contributes to increased corporate performance and future cash flows, then this belief may drive their preferences for gender-diverse board IPOs.

A second possibility is that investors prefer gender-diverse board firms for reasons that are not related to the expected cash flows of the company. Renneboog et al. (2007) suggest that investors receive non-monetary benefits from owning ethical funds, as their investment dollars are poten-

<sup>&</sup>lt;sup>4</sup>Specifically, Eckbo et al. (2021) argue that these quota studies are potentially flawed for at least two reasons: (1) it is difficult to correctly identify news events that significantly change the market's prior probability of a quota law and (2) because legal and regulatory shocks affect all sample firms simultaneously in calendar time, economic factors that drive stock returns tend to generate pervasive positive contemporaneous return correlations across securities, which necessitates correctly adjusting standard errors of abnormal stock returns for any contemporaneous cross-correlation of returns.

tially going towards causes that align with their ethical and social values. If an investor espouses a social value of, for example, increasing the (historically unavailable) opportunities for women to advance professionally, then they will likely express a preference for more female representation on corporate boards, even if such representation is unrelated to corporate performance. As a result, these investors may attribute a lower cost of capital to these firms, increasing their valuations of the firms regardless of the firms' expected future cash flows. Conversely, Fabozzi et al. (2008) show that investors demand higher expected returns from companies in "sin industries," such as the gaming, tobacco, and alcohol industries. The products and services provided by firms in these industries may not align with investors' ethical and social values, so they will need to be compensated for owning their shares of stock. While the information asymmetry discussed in Benveniste and Spindt (1989) is generally about the expected cash flows of the firm, the information provided by investors to underwriters during the book-building process could also be about their preferences for firm characteristics that are not related to cash flows but that are related to their ethical and social values. Given the rising demand for greater female representation on corporate boards, we seek to answer the following questions: does a significant relation exist between board gender diversity and IPO price formation, and what does this relation teach us about investor preferences for and valuations of gender-diverse board firms?

## **3.** Data Construction

To analyze the effects of board gender composition on IPO price formation, we use the Kenney-Patton Firm and Management Databases of Emerging Growth IPOs (Kenney and Patton, 2017).<sup>5</sup> This database provides us with biographical information for the directors of each firm at the time of the IPO. The database excludes IPOs from the following types of firms and filings: mutual funds, real estate investment trusts (REITs), asset acquisition or blank check companies, foreign F-1 filers, and all spin-offs and other firms that are not true emerging growth firms (such as firms formed purely to acquire other firms). Removing these non-emerging growth companies is important be-

<sup>&</sup>lt;sup>5</sup>While the name of their database suggests an end-point of 2010, the authors have updated their data to extend through 2018.

cause the role of directors in these companies is likely substantially different than in emerging growth companies. Directors function as monitors, ensuring managers pursue shareholders' interests, and advisors, to help management make the best real investment and operating decisions (Sandvik, 2020). Non-emerging growth companies, like shell companies, mutual funds, and blank check companies do not make typical real investment and operating decisions, so the value and influence of directors in these companies is likely to be different from those in emerging-growth companies. We merge the Kenney-Patton IPO sample with data from Thomson One and SDC, which allows us to identify the underwriters involved in underwriting the IPO and other IPO characteristics. The overlap between these two datasets results in a sample of 1,552 unique IPOs with issue dates from January 1st, 2000 to December 31st, 2018. We have non-missing Compustat financial data and IPO characteristic controls for 1,112 IPOs, which makes up our data sample.

We identify the gender composition of IPO firms' board of directors using the biographical information on each director provided in a firm's IPO prospectus. We search the biographies for gendered titles (e.g., Mr., Mrs., and Ms.) and for gendered pronouns (e.g., He and She), and we use these labels to classify individual directors as either male or female. In some instances, no gendered titles or pronouns are present in a biography, and in some cases both types of gendered words are present (e.g., when a biography mentions a director and their spouse). In these instances, we manually inspect the biographies and, in some cases, use Bloomberg, LinkedIn (which frequently has a photograph), or other search engines to fill in missing gender data. We also use first names to identify the gender of directors for whom we cannot find information elsewhere. When we compare our gender categorizations to those already in the Kenney-Patton database, we have agreement in 99.5% of the observations. We manually inspect the 0.5% of observations that are misaligned and use the methods described above to determine the final gender classification for each. For each IPO, we create a variable called *Gender-Diverse*, which equals one if there is at least one woman on the board, and zero otherwise.

Figure 1a shows the year-by-year trends in the number of IPOs in our sample. The year 2000 marked the high point, as this was at the height of the dot-com bubble, and we observe a dearth of IPOs in 2008 and 2009, at the trough of the Great Recession, where only 7 and 13 IPOs occurred, respectively, compared to the yearly average of 59. Figure 1b shows that the fraction of IPOs with gender-diverse boards was the smallest in 2008 and that it has steadily (almost monotonically) increased since then. This increase in female representation on the boards of IPO firms is likely due to several factors, including the SEC's 2010 requirement that public companies disclose the role that diversity considerations play when they select directors, along with other external pressures to increase board gender diversity.

Table 1 displays summary statistics for the 1,112 IPOs in our sample, of which 438 (39%) have gender-diverse boards. The average level of underpricing is 22.61%, which means that for the typical IPO, the stock price at the close of the first day of trading is 23% greater than the offer price. This level of underpricing is consistent with the underpricing levels documented in other studies (Willenborg et al., 2015; Blankespoor et al., 2017). The average amount of unrealized proceeds due to underpricing is \$30.75 million, the average offer price is \$14.67, and the average midpoint of the initial file price range is \$14.81.

Table 1 also displays summary statistics for the control variables used in our analyses. The main controls we use in our regression analyses are the fifteen robust determinants of IPO underpricing identified by Butler et al. (2014): ln(Sales), Offer Price Change, ln(News), Total Debt / Assets, IB Market Share, Avg. Underpricing<sub>[-30,-1]</sub>, Avg. Price Revision<sub>[-30,-1]</sub>, Prior Market Return, ln(Ret / Off), Offer Revision Flag, ln(Industry Mkt / Sales), ln(Offer Cap. / Sales), Avg. Industry Ret.<sub>[-30,-1]</sub>, Std. Industry Ret.<sub>[-30,-1]</sub>, and Avg. NASDAQ Ret.<sub>[-30,-1]</sub> (these and all other variables are defined in the Appendix). The authors show that the results of prior studies are subject to change when controlling for these determinants of IPO underpricing (e.g., Lowry and Schwert (2002)). We report summary statistics for these variables under the header "Main Controls" in

Table 1. In the year leading up to its IPO, the average firm in our sample realizes log sales of 3.84, experiences a change in offer price of -1%, and has a total debt to assets ratio of 0.14.

We also control for several of the other measures that Butler et al. (2014) show to be significant determinants of IPO underpricing in some of the models they employ, as well as the controls mentioned in Loughran and Ritter (2004). We report summary statistics for these variables under the header "Additional Controls" in Table 1. At the time of its IPO, the average firm in our sample has log assets of 4.59, is 12 years old, and has a market capitalization of \$743 million. In addition, 62% of the IPOs are backed by VC funding, 17% are internet stocks, 36% are considered technology companies, 73% are listed on the NASDAQ stock exchange, and 4% have female CEOs. We also tabulate summary statistics for several other control variables used in our analyses, including underwriter centrality measures, firm financial information, and director characteristics. Overall, we have a total of 57 control variables that we include in our regression specifications. The inclusion of these controls in our empirical tests reduces significant concerns regarding omitted variables bias, as they explicitly control for the significant determinants of underpricing documented in the prior literature, some of which may also be correlated with board gender diversity.

## 4. Effect of Board Gender Diversity on IPO Underpricing

As detailed in Section 2, board gender diversity will impact IPO underpricing if investors have preferences for gender-diverse boards that are not fully incorporated into the offer price of the IPO. We begin by estimating the relation between board gender diversity and IPO underpricing, and we test whether the relation has changed over time. We then present evidence to suggest that institutional investor demand drives the relation, and we discuss the role of underwriter network centrality in mitigating the underpricing effect.

## 4.1. Board Gender Diversity and Underpricing

We begin by regressing an IPO firm's issue date underpricing on an indicator variable, *Gender-Diverse*, that equals one if the firm's board has at least one woman on it, and zero otherwise. In all specifications, we include year fixed effects,  $\lambda_t$ , industry fixed effects,  $\gamma_j$ , and the fifteen

14

robust determinants of underpricing identified by Butler et al. (2014), represented by  $X_i$ . In some specifications, we include additional control variables in  $X_i$ . We estimate the following model using ordinary least squares:

Underpricing<sub>i</sub> = 
$$\alpha + \beta_1$$
Gender-Diverse<sub>i</sub> +  $\beta X_i + \lambda_t + \gamma_i + \varepsilon_i$ . (1)

The baseline results, controlling for year fixed effects, industry fixed effects, and the main Butler et al. (2014) controls, are displayed in Column (1) of Table 2. The estimate on *Gender-Diverse* is 4.924, and it is statistically significant at the 1% level. The magnitude of this estimate implies that gender-diverse board IPOs realize underpricing that is about 5 percentage points greater than do non-diverse board IPOs, which represents an increase in underpricing of 22% relative to the sample average reported in Table 1 (4.924 / 22.61 = 0.2178). Importantly, this positive relation between board gender diversity and IPO underpricing is not attributable to other previously documented determinants of underpricing, nor to time-invariant differences across industries, as we explicitly control for these.<sup>6</sup>

A natural concern when estimating the effects of board gender diversity on corporate outcomes is that firms that choose to have gender-diverse boards may differ from those that choose not to in ways that directly impact the outcomes of interest. While a careful selection of control variables can help mitigate omitted variables bias, more can be done to improve the comparability of gender-diverse board firms and non-diverse board firms. To do this, we perform the entropy balancing procedure proposed by Hainmueller (2012), which is a generalization of propensity score matching. The procedure weights the data to achieve ex ante covariate balance, adjusting for random and systematic inequalities in the variable distributions between the treatment and control groups. Entropy balancing is more flexible than other matching methods, as the estimated weights

<sup>&</sup>lt;sup>6</sup>We note that not all the controls in Column (1) load significantly. While Butler et al. (2014) find that all fifteen factors are significant determinants of underpricing, their sample used data from 1981–2007. So the difference in our results may be driven by the difference in sample period, as their findings would have been more heavily influenced by the wave of IPOs leading up to the dot-com bubble, which our sample excludes. In addition, we include year and industry fixed effects in our analysis, which may also absorb some of the explanatory power that the factors may have in the absence of these fixed effects controls.

vary smoothly, allowing all data to be retained and improving efficiency.<sup>7</sup> The covariates that we use to balance the treatment group (gender-diverse board IPOs) and control group (non-diverse board IPOs) are all the control variables used in Column (1). We re-estimate Equation (1) using the entropy-balanced sample, and we tabulate the results in Column (4) of Table 2. The estimate on *Gender-Diverse* continues to be significant at the 1% level, and the coefficient increases to 5.331. These results suggest that, when matching gender-diverse and non-diverse board IPOs based on their ex ante characteristics, gender-diverse boards IPOs realize significantly greater underpricing than do non-diverse board IPOs.

To further mitigate concerns about omitted variables bias, in Column (2), we control for a host of additional IPO, firm, and director characteristics. First, we include 9 additional controls that Butler et al. (2014) show to be determinants of underpricing using either the least absolute shrinkage and selection operator (Lasso) approach or the weighted average least squares (WALS) approach: ln(Assets), ln(Off / Out), Amended Offer Revision, Selling Fee / Proceeds, Pure Primary Dummy, Std. Underpricing<sub>[-30,-1]</sub>, Std. Price Revision<sub>[-30,-1]</sub>, Std. NASDAQ Ret.<sub>[-30,-1]</sub>, and NASDAQ Dummy. We also include the following controls, which are motivated by the prior literature (Hanley, 1993; Loughran and Ritter, 2002; Cornelli and Goldreich, 2003; Loughran and Ritter, 2004): In(Firm Age), Top Tier Underwriter, Share Overhang, VC Dummy, Internet Dummy, Tech Dummy, and Market Capitalization. These controls are meant to capture latent constructs that might simultaneously impact board gender diversity and underpricing. For example, larger, more mature firms may have better access to the female director labor market, and they may also incur greater underpricing if investors have a preference for large, mature firms. We control for Market Capitalization and ln(Firm Age) to account for this possibility. In addition, firms with gender-diverse boards may be differentially likely to employ a top-tier underwriter, and underwriter quality is likely to impact underpricing, so we control for *Top-Tier Underwriter*. The percentage of shares retained by the firm, *Share Overhang*, can impact underpricing and may be influenced by the board. We also

<sup>&</sup>lt;sup>7</sup>Entropy balancing has been used in other studies in accounting and finance (LaViers et al., Forthcoming; Mkrtchyan et al., 2022).

control for whether the firm has venture capital backing, VC Dummy, as VC investors generally enact some control over a firm's board structure, and their involvement in the IPO process could impact underpricing. Internet stocks and technology companies generally have greater female representation on their boards, and these firms tend to incur more underpricing (Bartov et al., 2002), so we control for Internet Dummy and Tech Dummy. We control for the gender of the CEO, as there is some evidence that women are superior negotiators when negotiating on behalf of others (Amanatullah and Morris, 2010; Bowles and Babcock, 2013), suggesting that female CEOs may bargain for a more favorable offer price. We control for the average network centrality of all the underwriters of the IPO, Avg. Centrality, and the centrality of the lead underwriter, Lead Centralitv.<sup>8</sup> We also include an array of director characteristic controls that are meant to capture director ability, experience, and education, as well as other aspects of board diversity, like age and ethnicity. We do this by parsing through director biographies in each IPO prospectus to identify the age and educational attainment of each director. We use the skillset taxonomy of Adams et al. (2018) to count the number of skills possessed by each director, and we use the length of each director's biography as a proxy for their overall experience level. We then create board-level variables that capture the average and standard deviation values of directors' age, number of skills, biography lengths, Master's degree attainment, and Doctorate degree attainment. Finally, we follow Flam et al. (2022) and use data from List Service Direct to identify the ethnicity, religion, and primarylanguage of each director, and we create board-level variables that capture the presence of directors from specific ethnic, religious, and primary-language groups. We also create board-level variables that capture the variations in these characteristics, which allow us to proxy for other dimensions of board diversity. Overall, we include 48 controls in this regression, along with 13 ethnic group controls, 11 religious group controls, and 34 primary-language group controls.

All these controls are included in the models used in Columns (2) and (5) of Table 2. The estimate on *Gender-Diverse* continues to be significant at the 1% level, and the coefficient increases

<sup>&</sup>lt;sup>8</sup>These are based on the *Degree* measure discussed by Bajo et al. (2016).

to 5.356 in Column (2). The results in Column (5) show that this effect is robust when using an entropy-balanced sample.

Finally, in Columns (3) and (6) we follow Glushkov et al. (2018) and control for various measures of the firm's profitability, growth opportunities, leverage, and liquidity in the year leading up to its IPO, leading to a grand total of 57 controls in our main regressions, along with the previously mentioned ethnic, religious, and primary-language group controls.<sup>9</sup> The estimates on *Gender-Diverse* in Columns (3) and (6) increase above 5.7 and are significant at the 1% level, representing an increase in underpricing of 25% relative to the sample average. We only have CSR score data for 652 of our sample firms, but when we re-estimate the model in Column (6) with the inclusion of a control for the firm's CSR score, the magnitude of the coefficient on *Gender-Diverse* increases to 6.0 and remains significant at the 5% level. Taken together, the results in Table 2 provide convincing evidence that gender-diverse board IPOs realize significantly greater underpricing than do non-diverse board IPOs. This relation is not due to omitted variables bias that stems from other known determinants of underpricing, other aspects of board diversity, other aspects of board experience and skill, industry differences, financial fundamentals, or CEO gender. That the relation is robust when controlling for all these factors and when using an entropy-balanced sample provides convincing evidence that board gender diversity leads to increased IPO underpricing.<sup>10</sup>

Though IPO underpricing is a widely documented phenomenon, this paper is the first to document that gender-diverse board IPOs experience even *greater* underpricing. The significant increase in underpricing realized by gender-diverse board IPOs relative to non-diverse board IPOs

<sup>&</sup>lt;sup>9</sup>We use this full set of controls in all subsequent analyses. Some control variables are not populated across all observations. We set these missing values to zero and include indicator variables into the regressions to denote which observations have missing values for particular control variables.

<sup>&</sup>lt;sup>10</sup>In Table A.1 we re-estimate the main regression models using—instead of the dummy *Gender-Diverse*—a variable that captures the fraction of the board that is represented by female directors, *Fraction Female*. Using the *Fraction Female* variable suggests that going from a fully male board to a fully female board would lead to increased underpricing of 23.6–32.1 percentage points. All of our subsequent results are qualitatively similar if we use the *Fraction Female* measure, rather than the *Gender-Diverse* measure. The *Gender-Diverse* measure provides more tractable inferences and it is more applicable to what we observe in real-world settings, which is why we prioritize it. Also, in 26 of the 438 IPOs in our sample with gender-diverse boards, the only woman on the board is also the CEO. If we relabel these IPOs as non-diverse—capturing the fact that no non-CEO board members are women—our underpricing results remain the same.

begs the question as to how much additional money these diverse board firms miss out on due to underpricing. To estimate this, we follow Loughran and Ritter (2002) and create the variable *Unrealized Proceeds*, measured as the price change from the offer price to the closing first-day market price, multiplied by the number of shares issued. We then re-estimate our regression models with *Unrealized Proceeds* as the dependent variable. We find that gender-diverse board IPOs incur approximately \$11 million more in unrealized proceeds than do non-diverse board IPOs, which is over 35% the sample mean.

#### 4.2. Board Gender Diversity and Underpricing Across Time

If the observed gender diversity underpricing effect is driven by investors' preferences for firms with female representation on their boards, then we would expect the effect to be greater in years when these preferences are stronger. To explore this, we plot in Figure 2 the unconditional mean levels of underpricing for gender-diverse and non-diverse board IPOs. The underpricing of gender-diverse and non-diverse board IPOs. The underpricing of gender-diverse and non-diverse board IPOs is quite similar in the 2000–2009 period, especially in the years after the burst of the dot-com bubble. Then in the first years of the 2010s, the average underpricing of gender-diverse board IPOs jumps upward, whereas the underpricing level of non-diverse board IPOs is also evidenced by formal structural break tests, where the supremum Wald test statistic is 10.68 (p-value = 0.0719). As such, we test whether the aggregate underpricing effect is significantly different in the 2010–2018 period than it is in the 2000–2009 period.

Table 3 reports these comparisons in effects across time. In Column (1), we re-estimate our main specification among only IPOs in the 2000s using the same full set of controls as in Columns (3) and (6) of Table 2. In Column (2), we use only IPOs in the 2010s. The coefficient on *Gender-Diverse* is small and insignificant in Column (1), whereas it is large and statistically significant at the 5% level in Column (2). The magnitude of the coefficient in Column (2) indicates that gender-diverse board IPOs in the 2010s realize greater underpricing of 8.6 percentage points, relative to non-diverse board IPOs. This underpricing effects equates to gender-diverse board IPOs incurring

\$20.94 million more in unrealized IPO proceeds. Columns (4) and (5) show that these results remain essentially unchanged when we use entropy-balanced data. In Columns (3) and (6), we use the full sample of IPOs and include the interaction between *Gender-Diverse* and *Post*, which equals one for IPOs in the 2010s and zero otherwise. This is an estimation of the following model:

Underpricing<sub>i</sub> = 
$$\alpha + \beta_1$$
Gender-Diverse<sub>i</sub> +  $\beta_2$ Gender-Diverse<sub>i</sub> × Post<sub>i</sub> +  $\beta_i + \lambda_i + \gamma_i + \varepsilon_i$ , (2)

which we henceforth refer to as our interaction model. The positive, significant estimates on *Gender-Diverse*  $\times$  *Post* in Columns (3) and (6) indicate that the gender diversity underpricing effect is significantly greater in the 2010s than it is in the 2000s. To ensure that this change in diversity-related underpricing across the decades is not caused by changes in the observable characteristics of gender-diverse board IPOs versus non-diverse board IPOs, we use a fully saturated model that includes interactions between all of our control variables and the *Post* indicator. Thus, the observed increase in underpricing among gender-diverse board IPOs relative to non-diverse board IPOs is *not* attributable to changes in the ethnic diversity of the boards, the experience level of the boards, or other observable board characteristics that may have changed across the decades. Taken together, the trends in Figure 2 and the results in Table 3 provide clear evidence that the observed underpricing effect is almost entirely driven by IPOs in the 2010–2018 period, when investor demand for board gender diversity has been substantial (Gormley et al., 2020).

## 4.3. Does Investor Demand Drive the Underpricing Effect?

As the gender diversity underpricing effect is negligible in the 2000–2009 period but prominent in the 2010–2018 period, we investigate whether investor demand for board gender diversity changed during this time, which could explain the emergence of the underpricing effect in the recent decade. To do this, we consider how investor trading behavior on the first day of trading changed across the decades. Specifically, we estimate the interactive effect on underpricing of board gender diversity and institutional investor trading behavior on the first day of trading after the IPO. We follow Krigman et al. (1999) and proxy for institutional investor trades by identifying block trades on the first trade day using TAQ data. We create a variable, *Large Trades*, which equals the number of

trades of 10,000 shares or more.<sup>11</sup> We then include this variable and its interaction with *Gender-Diverse* into the main regression specifications.

Columns (1) and (2) of Table 4 display the results within decade subsets, where we use an entropy-balanced sample and include all the controls used in Columns (3) and (6) of Table 2. The main takeaway comes from comparing the negative, statistically significant estimate on *Gender-Diverse* × *Large Trades* in Column (1) to the positive, significant estimate in Column (2). These results show that block trading behavior—most likely performed by institutional investors contributes to decreased (increased) underpricing among gender-diverse board IPOs in the 2000– 2009 (2010–2018) period. The contrast suggests that, on the first trade day after IPO, institutional investors applied selling pressure to gender-diverse board stocks in the 2000s and buying pressure in the 2010s, which is evidence of increased demand for the stock of gender-diverse board firms in the latter period. Column (3) presents the results of a fully saturated model that includes the triple interaction between *Gender-Diverse, Large Trades*, and *Post*, as well as interaction terms between all the controls and *Post*. The estimate on *Gender-Diverse* × *Large Trades* × *Post* is positive and statistically significant, indicating that the impact of institutional traders on the underpricing of gender-diverse board IPOs is significantly more positive in the 2010s than it is in the 2000s.

To show that the relation between institutional investor trading behavior and the underpricing of gender-diverse board IPOs is not simply capturing a relation between underpricing and the number of trades made, regardless of trade size, we repeat these estimations using the variable *Small Trades*, which equals the number of trades of less than 1,000 shares. Note, we do not classify these small trades as strictly retail trades, as institutional investors are known to break their large trades up into smaller trades to avoid impacting stock prices (Cready et al., 2014; Barber et al., 2022). We tabulate these results in Columns (4)–(6) of Table 4. The estimates on *Gender-Diverse* × *Small Trades* in both Column (4) and Column (5) are close to zero and statistically insignificant, and the estimate on *Gender-Diverse* × *Small Trades* × *Post* in Column (6) is also

<sup>&</sup>lt;sup>11</sup>This approach also aligns with the findings in Barber et al. (2021), which show that retail traders rarely make trades that exceed \$100,000. Given that the offer prices of most of the IPOs in our sample exceed \$10, a 10,000-share trade would exceed \$100,000, indicating that it is very likely being made by an institutional trader.

small and insignificant. These results suggest that the findings in Columns (1)–(3) are not simply capturing a general effect of the number of trades of any size on underpricing. Taken together, the results in Table 4 provide evidence that institutional investors increased their demand for gender-diverse board firms in the recent decade, and this increased demand contributed to the underpricing experienced by gender-diverse board IPOs.

To provide additional evidence that institutional investor demand is the likely driver of the observed underpricing effect, we examine the relation between IPO board gender diversity and institutional ownership. We use two different ownership measures in this analysis: Percent Inst. Own, which equals the fraction of a firm's shares owned by institutional investors according to the first ownership report after the IPO, and Percent Big Three Own, which equals the fraction of a firm's shares owned by either BlackRock, State Street, or Vanguard according to the first ownership report after the IPO. In Column (1) of Table 5, we consider only IPOs in the 2000s and regress Percent Inst. Own on Gender-Diverse and all the controls used in Columns (3) and (6) of Table 2. In Column (2) we consider only IPOs in the 2010s, and in Column (3) we consider all IPOs and include the interaction of Gender-Diverse and Post into the model, as well as interaction terms between all the controls and *Post*. We use an entropy-balanced sample in all specifications. The results indicate that the institutional ownership of gender-diverse board IPOs was less than that of non-diverse board IPOs in the 2000s, and then this relation flipped in the 2010s. The positive coefficient on *Gender-Diverse*  $\times$  *Post* in Column (3) indicates that the institutional ownership of gender-diverse board IPOs increased significantly across the two time periods. The results in Columns (4)–(6) show that this change in ownership structure across the decades holds when focusing specifically on the shareholdings of BlackRock, State Street, and Vanguard. Taken together, these findings provide additional evidence that institutional investor demand for genderdiverse board firms increased in the most recent decade, and this increase in demand is likely the cause of the increased underpricing realized by gender-diverse board IPOs.

#### 4.4. Board Gender Diversity and Early-Stage IPO Price Formation

Our evidence thus far indicates that gender-diverse board IPOs realize significantly greater underpricing than do non-diverse board IPOs, that this underpricing effect is almost entirely driven by IPOs in the 2010–2018 period, and that institutional investor demand is the mechanism that drives the observed underpricing. Next we investigate whether board gender diversity impacts the earlystage price formation of IPOs. This analysis allows us to rule out potential alternative explanations for the underpricing effect. We also use this analysis to draw inference as to whether the underpricing effect is being driven by investors who are involved in the book-building process or those who only access shares on the first day of trading.

We follow Bartov et al. (2002), Ecker (2014), Willenborg et al. (2015), and Blankespoor et al. (2017) by examining IPO pricing at earlier stages in the process, and we tabulate the results in Table 6. We consider the initial file price of the IPO (i.e., the mid-point of the initial file price range) in Panel A, the percent change in price from the initial file price to the offer price in Panel B, and the final offer price of the IPO in Panel C. Across all panels, Column (1) reports estimations of Equation (1) using all IPOs, Column (2) restricts to IPOs in the 2000s, and Column (3) restricts to IPOs in the 2010s. Column (4) reports estimations of the interaction model. We use an entropy-balanced sample in every specification, and we include all the previously mentioned control variables and, in Column (4) only, the interactions between these variables and the *Post* indicator.

One potential alternative explanation for the underpricing effect is that underwriters might systematically undervalue gender-diverse board IPOs. This could be due to explicit or implicit biases against women, which have been documented previously among financial institutions. For example, Thébaud and Sharkey (2015) show that female-led small businesses had a more difficult time accessing external financing than did male-led small businesses after the Great Recession. Similarly, Cozarenco and Szafarz (2018) show that female borrowers of micro-financing loans are treated more harshly than male borrowers. In addition, Egan et al. (2017) present evidence that suggests that women in the finance industry are punished more severely when they engage in misconduct than are their male colleagues who engage in similar misconduct. If systemic undervaluation were occurring, we would expect to find a negative effect of board gender diversity on the early-stage pricing of IPOs. We do not find any evidence of this behavior, as none of the estimates on *Gender-Diverse* in Table 6 are negative. As such, we find no evidence of discrimination towards gender-diverse board firms in the IPO price formation process.

We next investigate whether the underpricing effect is more likely driven by institutional investors who received IPO shares and also bought additional shares on the first trading day or by institutional investors who were not a part of the book-building process, who could only access shares on the first trading day. If the institutional investors who were invited to take part in the book-building process communicated their excess demand for the shares of gender-diverse board IPOs, we would expect to see a greater offer price change among these IPOs in Panel B, as underwriters would have used this information to adjust the offer price upwards. We do not find evidence of this, as the estimates on *Gender-Diverse* in Panel B are not statistically significant. Alternatively, these investors could have chosen to keep their preferences for board gender diversity private to prevent underwriters from increasing the offer price in response to excess demand for IPO shares. But then these investors would have had to have achieved their desired share allocation by purchasing the firm's stock on the first day of trading, where they bore the risk of purchasing the stock at an even higher price if buy-side demand from other investors bid up the price of the stock.

A more likely explanation is that the underpricing effect is being driven by institutional investors who are *not* involved in the book-building process. These investors are not able to communicate their preferences for board gender diversity to the underwriters of the IPO, so early-stage IPO pricing is unlikely to be impacted by their demand for the firm's shares. This is consistent with the findings in Table 6. These investors may be fund managers who have not yet formed strong enough relationships with investment banks to be granted access to IPO shares, such as, for

example, managers of relatively new or niche funds, like those with an ESG focus. Without data on which investors were allocated IPO shares and which purchased shares on the first day of trading, it is difficult to provide direct evidence for or against this explanation. One possible approach is to consider IPOs that occur on the same day that funds use as the last day in the quarter in their holdings reports. We could then reasonably assume that these funds were allocated IPO shares (Reuter, 2006). Unfortunately, only 4 of the IPOs in our sample occur on one of the four most common fiscal-quarter-end dates: March 31st, June 30th, September 30th, or December 31st. While this small sample size prevents us from making precise inferences, we find suggestive evidence that is consistent with the notion that investors who were not allocated IPO shares buy up shares on the first day of trading, which likely drives the underpricing effect. For these four IPOs in the sample with IPO dates that coincide with fiscal-quarter ends, there are fewer unique funds that own shares of gender-diverse board IPOs (11.5, on average) than of non-diverse board IPOs (53, on average). If we then consider IPOs that occur one to two days before the fiscal-quarter end, wherein non-IPO participants would have had time to purchase the post-IPO shares of stock, gender-diverse board firms (N = 12) are owned by 30.3 unique funds, on average, whereas non-diverse board firms (N= 20) are owned by 42.3 unique funds, on average. While this is a coarse comparison of different IPOs, the increase in the number of unique funds that own gender-diverse board IPOs and the decrease in the number of funds that own non-diverse board IPOs is consistent with the hypothesis that a larger number of unique funds acquire shares of gender-diverse board firms in the post-IPO secondary market than of non-diverse board firms, which is a potential explanation for the observed underpricing effect.

### 4.5. Impact of Underwriter Network Centrality on the Underpricing Effect

A natural next question is whether underwriters are able to attenuate the observed underpricing effect over time. This could occur if underwriters increase their supply of institutional investor clients over time, especially if diversity-focused investors are added to the supply, or if underwriters learn how to more accurately incorporate preferences for board gender diversity into the offer prices of IPOs. In either case, we hypothesize that underwriters with high degrees of network

centrality among other investment banks are the most likely to mitigate underpricing, either by inviting diversity-focused investors to the book-building process or by learning how to efficiently incorporate diversity preferences into prices. We run multiple tests to determine whether underwriter network centrality impacts the gender diversity underpricing effect.

To do this, we build the *Degree* measure used in Bajo et al. (2016), which they refer to as the most intuitive and straightforward centrality measure. For each IPO, we consider each underwriter of the deal. We then look back five years (including the year of the IPO) and identify how many unique IPO underwriters exist in the sample (N). We then note how many unique underwriters the focal underwriter was connected to by being part of the same syndicate of underwriters on IPOs in that five-year period. This value becomes n. For a given underwriter-year, the Degree measure equals n / N. Then for each IPO, we identify the average value of *Degree* across its underwriters and we create an indicator variable, High Centrality, that equals one if this average value of Degree is above the sample median, and zero otherwise. We then interact this indicator variable with Gender-Diverse  $\times$  Post in the interaction model. The estimate on Gender-Diverse  $\times$  High Centrality  $\times$  Post in Column (1) of Table 7 is negative and statistically significant. This suggests that increased network centrality among the underwriters of the IPO reduces the gender diversity underpricing effect. Said another way, well-connected underwriters appear to be better able to accurately incorporate investor preferences for board gender diversity into the offer price of an IPO, potentially because they know to invite diversity-focused investors to the book-building process.

In Column (2), we break up the indicator *Post* into two separate indicators: (2010–2013), which equals one for IPOs from 2010–2013 and zero otherwise, and (2014–2018), which equals one for IPOs from 2014–2018 and zero otherwise. We do this to see if underwriter centrality mitigates the underpricing effect across the entire 2010–2018 time period, or if it takes underwriters time to connect with diversity-focused investors and to incorporate their preferences into offer prices. The estimate on *Gender-Diverse* × *High Centrality* × (2010–2013) is negative, but it is

not statistically significant, whereas the estimate on *Gender-Diverse* × *High Centrality* × (2014–2018) is negative and significant. These results suggest that it may have taken some time for underwriters with high levels of network centrality to connect with diversity-focused investors and incorporate their preferences for gender diversity into the offer prices of IPOs. In contrast, the positive, significant estimates on *Gender-Diverse* × *Post* in Column (1) and on *Gender-Diverse* × (2010–2013) and *Gender-Diverse* × (2014–2018) in Column (2) suggest that poorly connected underwriters contribute substantially to the gender diversity underpricing effect across the entire 2010–2018 period.

### 5. Alternative Explanations

In Section 4, we presented robust evidence that gender-diverse board IPOs realize significantly greater underpricing than do non-diverse board IPOs. We found evidence that this effect is driven by the demand of institutional investors for gender-diverse board firms. We also discussed evidence that suggests well-connected underwriters are better able to reduce the underpricing effect. In this section, we show that board gender diversity does not appear to impact future profitability or the likelihood of value-destroying corporate events. Then we present evidence that the underpricing effect is not due to market inefficiencies. To finish, we present evidence against the possibility that board gender diversity is a window-dressing effort used by firms to elicit attention from investors.

#### 5.1. Future Profitability and Value-Destroying Events

One hypothesis as to why institutional investors value gender-diverse boards is that female directors add value above and beyond what their male counterparts contribute—that is, there are direct cash flow consequences to women being on boards. For example, gender-diverse boards could act as a substitute mechanism for corporate governance that would be otherwise weak (Gul et al., 2011). Alternatively, if female leaders are less overconfident or more risk-averse than male leaders (Ge et al., 2011; Carter et al., 2017), then having more women on the board may reduce negative consequences such as over-investment and excessive risk-taking. Furthermore, diverse leadership may send a positive signal about a firm's ability to attract and retain a diverse talent pool of em-

ployees (Athey et al., 2000) or attract customers, especially if the media focuses attention on a firm's lack of gender diversity. In addition, employee responses to a firm's stance on diversity can meaningfully influence productivity and firm value (Mkrtchyan et al., 2022). Hence, this explanation would suggest that investment banks may not fully incorporate these possible cash flow benefits of gender diversity into the offer price, leading to underpricing.<sup>12</sup>

If there are cash flow benefits to firms from having gender-diverse boards, then gender-diverse board firms are likely to have superior operating performance. Hence, we examine the effect of board gender diversity on the long-run accounting performance of the IPO firms after the IPO. To measure accounting performance, we estimate each firm's industry- and size-adjusted return on assets (ROA) one year after the IPO.<sup>13</sup> We regress these ROA values on the same models used to populate Columns (4)–(6) of Table 3, which include all previously mentioned control variables and employ an entropy-balanced sample. The results of these estimates on *Gender-Diverse* in both time periods in Columns (1) and (2), and the differential effect between time periods is insignificant in Column (3). This suggests that board gender diversity at the time of the IPO is not related to future operating performance levels.

An alternate channel through which female directors might add value to the board is by preventing rare, value-destroying events such as accounting restatements and class action lawsuits. The mitigation of potentially harmful events will not necessarily show up in operating performance, but it may still benefit firm value. To test this, we gather data from the Audit Analytics database to identify instances of restatements incurred by the firm and class action lawsuits filed against the company. For each IPO in our sample, we sum up the number of accounting restatements incurred by the firm in the five years after IPO, and we sum up the number of instances in which the firm was named as a defendant in a class action lawsuit in the five years after IPO. We then separately set the accounting restatement and lawsuit variables as the dependent variables in our models. The

<sup>&</sup>lt;sup>12</sup>BlackRock, State Street, and Vanguard all articulated the belief that board gender diversity increases the effectiveness of the board, which could lead to improved corporate performance.

<sup>&</sup>lt;sup>13</sup>The results are similar if we consider two-year, three-year, and four-year ROA values.

results in Panel B of Table 8 show that board gender diversity at the time of IPO is not significantly related to the number of future accounting restatements incurred by the firm. Similarly, the results in Panel C suggest that gender-diverse board firms are no more or less likely to be the defendants in class action lawsuits. Taken together, all our tests suggest that, while gender-diverse board IPOs realize significantly greater underpricing relative to non-diverse board IPOs, the underpricing effect is not likely driven by expectations of differences in long-run firm performance or the likelihood of value-destroying corporate events.

#### 5.2. Market efficiency

Next we examine whether the initial underpricing is followed by additional excess returns in the weeks following the IPO, a test of whether markets are efficient on the first day of trading. If markets overreacted on the first day of trading, the diversity effect may well disappear in the following weeks. In contrast, if institutional investors are superior investors because they have better information about future cash flows, excess returns should increase. To test this, we measure the buy-and-hold abnormal returns realized by investors who purchase the IPO firm's shares on the first trading date and hold for five, ten, or twenty-five days. We use the value-weighted CRSP market index as the benchmark to measure abnormal returns. We then use these short-run return values as the dependent variables in regression specifications that mimic those used previously. We report the results in Table 9. The coefficients on *Gender-Diverse* and *Gender-Diverse* × *Post* are small and statistically insignificant in every column and panel, suggesting that IPO board gender diversity does not affect short-run performance, nor is performance affected differently in the 2010s than in the 2000s. These null effects also suggest that there are no meaningful stock price reversals following the initial trade day underpricing. This indicates that investor demand for gender-diverse board shares is efficiently worked into the stock price on the first day of trading.

### 5.3. Board Gender Composition as Potential Window-Dressing

A final consideration is whether firms use board gender diversity opportunistically at the time of the IPO to attract attention from institutional investors. First, we consider whether firms add female directors to the board in anticipation of an IPO. We use directors' biographies provided in the IPO prospectuses to identify when directors were first appointed to the board. We find that the average male director has served on the board of directors for 3.75 years while the average female director has served on the board of directors for 3.36 years at the time of the IPO. The difference between these averages is not statistically significant. This suggests that firms with gender-diverse boards at the time of the IPO are unlikely to be placing women on the boards of directors immediately before their initial public offering.

We then examine if firms adjust board composition to be less diverse in the years that follow the IPO. To do so, we use data from BoardEx to identify the gender composition of our IPO firms as reported in their first and second post-IPO proxy statements. If firms are opportunistically boosting their boards' gender diversity at the time of the IPO to appeal to the demands of particular investors and then replacing female directors with male directors post-IPO, we would expect to see an overall reduction in the fraction of gender-diverse boards in the years following the IPO. We do not find meaningful evidence of this behavior.

Among firms with a woman on the board at the time of the IPO, 93.4% continue to have at least one woman on the board in their first post-IPO proxy statement, and 90% have at least one woman on the board according to their second post-IPO proxy statement. In contrast, only 80% of firms with no women on the board at the time of the IPO continue to have no women on the board according to their second post-IPO proxy statement. So, while a small percentage of gender-diverse board IPOs become non-diverse in the subsequent years, a greater percentage of non-diverse boards at the time of the IPO become diverse in the two years following the IPO. Taken together, it does not appear to be the case that gender diversity at the time of the IPO is simply window-dressing meant to attract attention from institutional investors.

## 6. Conclusion

In this paper, we document a gender diversity effect in the level of underpricing for U.S. IPOs over the past decade. IPOs with at least one woman on the board are significantly more underpriced than

30

IPOs with all-male boards. The results are economically significant: over the last decade, firms with gender-diverse boards experience an 8.6 percentage point larger level of underpricing, resulting in, on average, \$20.94 million more in unrealized IPO proceeds. These results are robust when we use an entropy-balanced sample and when we control for a wide array of possible confounding factors that may jointly affect board gender diversity and underpricing, which substantially reduces omitted variables bias concerns. The effect appears to be driven by excess institutional investor demand, likely from investors who were not involved in the book-building process. We also find evidence that well-connected investment banks more efficiently price these preferences for board gender diversity.

We do not find empirical support for alternative cash flow-relevant explanations for the underpricing effect. For example, over the years subsequent to the IPO, we do not find that the industryand size-adjusted return on assets is higher for gender-diverse board firms than for non-diverse board firms. So, the results do not seem to be driven by valuation models underestimating the expected profitability from board gender diversity—a claim often made in research conducted by practitioners. The fact that profitability is unrelated to board gender diversity lowers concerns about endogeneity, as one argument frequently made in diversity studies is that highly profitable firms hire more women. We also find no evidence that gender-diverse board firms incur a different frequency of value-destroying events such as future accounting restatements or class action lawsuits.

Investor demand for greater board gender diversity is a relatively recent phenomenon (Gormley et al., 2020), which may explain why the underpricing effect does not show up in the early 2000s. One possible explanation for the demand shift could be that investors have become more comfortable with diversity following the increase in the experience levels of female board members in recent years. However, we find that the underpricing effect is robust when controlling for changes in director experience, educational attainment, and skillsets across the decades. We also do not find any evidence that firms opportunistically change the gender composition of their boards to attract

attention from institutional investors. Our results suggest that investor demand for gender-diverse board firms may be due to preferences that are unrelated to corporate performance, similar to the non-monetary benefits that investors enjoy from owning more ethical stocks (Renneboog et al., 2007).

A final takeaway is that, over the past decade, institutional investors and firms have placed increased emphasis on stakeholder value maximization, diversity, and other CSR-related topics (Graham, 2022). There is a considerable debate in both the academic literature and the popular press on whether these issues are value-relevant. Our results show that one such factor, board gender diversity, appears to matter in corporate financing because large institutional investors, and perhaps others, believe it is important, even though we find little evidence that it is associated with profitability. As such, it is likely to become necessary for firms, especially small growth firms and those considering an IPO, to be proactive in addressing these non-pecuniary societal preferences, lest they be unable to receive the external financing necessary for future growth.
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#### Figure 1: IPO Trends Over Time





#### (b) Fraction of Gender-Diverse Board IPOs



*Notes:* Figure (a) displays trends in the number of IPOs in our sample each year. Figure (b) displays trends in the fraction of IPOs with gender-diverse boards each year. IPOs are defined as having a gender-diverse board if at least one woman serves on the board at the time of the IPO.



Figure 2: Trends in IPO Underpricing by Board Gender Diversity

*Notes:* This figure plots the unconditional mean levels of underpricing for gender-diverse and non-diverse board IPOs across time, along with 95% confidence intervals. IPOs are bucketed into two-year bins to limit noise in the years in which relatively few IPOs occur.

	Summary Statistics					
	N	Mean	Std. Dev.	25%	50%	75%
Main Regressor and Outcome	es					
Gender-Diverse	1,112	0.39	0.49	0.00	0.00	1.00
Underpricing	1,112	22.61	37.37	0.61	14.36	33.17
Unrealized Proceeds	1,112	30.75	103.81	0.38	12.22	37.17
Offer Price	1,112	14.67	6.03	11.00	14.00	17.00
Initial Midpoint	1,112	14.81	5.09	12.00	14.50	16.00
Main Controls	,					
ln(Sales)	1,110	3.84	2.55	3.04	4.30	5.29
Offer Price Change	1,112	-0.01	0.22	-0.13	0.00	0.11
ln(News)	1,112	1.88	1.83	0.00	1.61	3.53
Total Debt / Assets	1,112	0.14	0.22	0.00	0.03	0.20
IB Market Share	1,112	0.48	0.40	0.11	0.25	1.00
Avg. Underpricing $[-30,-1]$	1,112	0.24	0.22	0.11	0.19	0.31
Avg. Price Revision $_{[-30,-1]}$	1,112	0.00	0.13	-0.07	0.00	0.06
Prior Market Return	1,112	0.01	0.04	-0.01	0.01	0.03
ln(Ret / Off)	1,112	1.32	0.55	1.04	1.35	1.65
Offer Revision Flag	1,112	0.00	0.04	0.00	0.00	0.00
ln(Industry Mkt / Sales)	1,112	0.73	1.12	0.01	0.67	1.18
ln(Offer Cap. / Sales)	1,110	15.96	2.33	14.65	15.52	16.68
Avg. Industry Ret. $[-30,-1]$	1,112	0.07	0.28	-0.09	0.08	0.22
Std. Industry Ret. $[-30,-1]$	1,112	1.28	0.67	0.85	1.09	1.54
Avg. NASDAQ Ret. $[-30, -1]$	1,112	0.00	0.00	0.00	0.00	0.00
Additional Controls	,					
ln(Assets)	1,112	4.59	1.62	3.50	4.35	5.62
ln(Firm Age)	1,112	2.48	0.76	1.95	2.40	2.83
Top Tier Underwriter	1,112	0.36	0.48	0.00	0.00	1.00
Share Overhang	1,112	2.89	2.00	1.66	2.62	3.67
VC Dummy	1,112	0.62	0.49	0.00	1.00	1.00
Internet Dummy	1,112	0.17	0.38	0.00	0.00	0.00
Tech Dummy	1,112	0.36	0.48	0.00	0.00	1.00
NASDAQ Dummy	1,112	0.73	0.44	0.00	1.00	1.00
Market Capitalization	1,112	743.17	2646.77	222.53	358.23	678.01
Female CEO	1,112	0.04	0.20	0.00	0.00	0.00
Std. Underpricing $[-30,-1]$	1,112	0.26	0.24	0.13	0.21	0.32
Std. Price Revision $[-30, -1]$	1,112	0.17	0.11	0.09	0.16	0.22
Std. NASDAQ Ret. $[-30, -1]$	1,112	0.01	0.01	0.01	0.01	0.01
ln(Off / Out)	1,112	0.03	0.06	0.00	0.00	0.04
Amended Offer Revision	1,112	0.00	0.14	-0.08	0.00	0.08
Selling Fee / Proceeds	1,112	1.03	1.47	0.00	1.15	1.40
Pure Primary Dummy	1,112	0.65	0.48	0.00	1.00	1.00

Table 1Summary Statistics

40

	Ν	Mean	Std. Dev.	25%	50%	75%	
Centrality and Ownership Variables							
Avg. Underwriter Centrality	1,112	0.24	0.16	0.10	0.22	0.39	
Lead Underwriter Centrality	1,112	0.26	0.18	0.10	0.22	0.44	
Percent Inst. Own	1,046	0.37	0.28	0.19	0.29	0.47	
Percent Big Three	1,046	0.01	0.03	0.00	0.00	0.02	
Financial and CSR Controls							
Operating CF / CAPEX	1,100	-11.56	1870.38	-8.50	-0.94	1.07	
Operating ROA	1,010	-0.53	2.83	-0.55	-0.01	0.12	
R&D / Assets	1,112	0.21	0.49	0.00	0.09	0.29	
PPE / Assets	1,108	0.17	0.20	0.04	0.10	0.21	
Total Debt / Assets	1,112	0.14	0.22	0.00	0.03	0.20	
Debt / EBITDA	1,100	2.04	22.56	-0.04	0.00	1.96	
Debt / NWC	1,014	0.35	45.85	0.00	0.03	1.10	
Current Ratio	1,019	2.47	2.95	1.04	1.58	2.69	
Quick Ratio	1,011	2.23	2.95	0.86	1.28	2.44	
Cash Ratio	1,018	1.61	2.96	0.23	0.64	1.56	
CSR Score	652	10.53	1.20	10.00	11.00	11.00	
Director Characteristics							
Fraction Female	1,112	0.07	0.10	0.00	0.00	0.14	
Avg. Director Age	1,077	52.70	5.29	49.14	52.64	56.29	
Avg. Director Skills	1,111	2.52	1.07	1.71	2.43	3.25	
Avg. Director Bio. Length	1,111	929.56	319.62	688.38	889.50	1133.2	
Avg. Directors with Doctorate	1,111	0.16	0.19	0.00	0.13	0.25	
Avg. Directors with Masters	1,111	0.31	0.24	0.09	0.29	0.50	
Std. Director Age	1,070	9.04	2.73	7.09	9.12	10.95	
Std. Director Skills	1,107	1.32	0.48	1.00	1.26	1.59	
Std. Director Bio. Length	1,107	259.52	123.76	178.24	236.98	319.92	
Std. Directors with Doctorate	1,107	0.25	0.23	0.00	0.35	0.46	
Std. Directors with Masters	1,107	0.36	0.21	0.30	0.46	0.52	
Std. Ethnicity	1,107	2.69	1.47	1.96	2.86	3.76	
Std. Religion	1,107	3.28	1.10	3.02	3.58	3.95	
Std. Language	1,107	1.30	2.49	0.00	0.00	1.79	

Summary Statistics (continued)

*Notes:* This table displays summary statistics of the IPO, firm, and director characteristics of the IPOs in our sample. Variables are defined in the Appendix.

	S	tandard Samp	le	Entroj	Entropy-Balanced Sample		
	(1)	(2)	(3)	(4)	(5)	(6)	
Gender-Diverse	4.924***	5.356***	5.727***	5.331***	5.495***	5.712***	
	(3.138)	(3.277)	(3.414)	(3.327)	(3.298)	(3.320)	
ln(Sales)	0.586	5.392*	5.207*	1.453	5.325**	5.294**	
	(0.543)	(1.865)	(1.854)	(1.252)	(2.001)	(2.038)	
Offer Price Revision	87.631***	86.369***	84.248***	66.907***	58.446***	56.523***	
	(5.083)	(3.785)	(3.658)	(6.510)	(4.304)	(4.137)	
ln(News)	0.828	0.557	0.649	0.545	0.474	0.523	
	(1.182)	(0.737)	(0.831)	(0.741)	(0.599)	(0.645)	
Total Debt / Assets	-6.542*	-4.661	-4.449	-9.583**	-7.011	-7.388	
	(-1.750)	(-1.110)	(-1.081)	(-2.227)	(-1.423)	(-1.492)	
IB Market Share	-2.175	-3.462	-3.948	-1.850	-3.144	-3.237	
	(-0.829)	(-1.101)	(-1.249)	(-0.712)	(-1.051)	(-1.066)	
Avg. Underpricing $[-30,-1]$	-10.493	-21.124*	-20.316*	-5.736	-14.894	-15.323	
[, _]	(-1.267)	(-1.681)	(-1.714)	(-0.786)	(-1.277)	(-1.364)	
Avg. Price Revision $[-30,-1]$	-0.423	7.768	7.817	1.305	6.870	8.315	
	(-0.040)	(0.644)	(0.675)	(0.135)	(0.635)	(0.787)	
Prior Market Return	6.806	-8.275	-9.705	8.943	2.298	-1.040	
	(0.167)	(-0.172)	(-0.205)	(0.200)	(0.044)	(-0.020)	
ln(Ret / Off)	2.949	-3.652	-4.118	3.422	-0.355	-0.847	
	(1.161)	(-0.599)	(-0.682)	(1.461)	(-0.069)	(-0.167)	
Offer Revision Flag	-70.014***	-85.805***	-82.990***	-62.996***	-70.051***	-64.128***	
C	(-3.403)	(-3.246)	(-3.047)	(-3.723)	(-2.953)	(-2.878)	
ln(Industry Mkt / Sales)	0.613	0.711	0.386	0.921	1.220	0.904	
· · · ·	(0.802)	(0.923)	(0.458)	(1.209)	(1.589)	(1.060)	
ln(Offer Cap. / Sales)	1.026	5.492**	5.675**	1.492	5.076**	5.303**	
	(0.847)	(2.137)	(2.182)	(1.280)	(2.153)	(2.260)	
Avg. Industry Ret. $[-30,-1]$	-3.489	-1.806	-1.947	-2.470	-0.143	-0.522	
	(-0.960)	(-0.469)	(-0.518)	(-0.653)	(-0.039)	(-0.141)	
Std. Industry Ret.[-30,-1]	1.967	0.567	0.490	1.198	0.683	0.308	
	(0.999)	(0.335)	(0.275)	(0.716)	(0.427)	(0.186)	
Avg. NASDAQ Ret. $[-30,-1]$	13.989**	15.257**	15.135**	14.852**	14.331*	14.282*	
	(2.487)	(2.032)	(2.181)	(2.010)	(1.728)	(1.855)	
Year & Industry Fixed Effects	l l l l l l l l l l l l l l l l l l l	Ì√ ́	`✓´	) 🗸 (	`✓´	Ì√Í	
Director Characteristic Con.		$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$	
Loughran and Ritter (2004) Con.		$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$	
Glushkov et al. (2018) Con.			$\checkmark$			$\checkmark$	
Adj. R-Square	0.421	0.435	0.433	0.357	0.375	0.375	
Observations	1,112	1,112	1,112	1,112	1,112	1,112	

Table 2Effect of Board Gender Diversity on IPO Underpricing

*Notes:* The dependent variable in all columns is an IPO's underpricing on the first trading date. The focal regressor is the indicator variable *Gender-Diverse*. We control for the 15 main determinants of underpricing mentioned by Butler et al. (2014), year fixed effects, and industry fixed effects in all columns. In Columns (2) and (5) we also control for 33 additional determinants of underpricing, director characteristics, and firm characteristics, including those mentioned by Loughran and Ritter (2004), along with 13 ethnic group controls, 11 religious group controls, and 34 primary-language group controls. In Columns (3) and (6) we include 9 financial controls mentioned by Glushkov et al. (2018). Columns (4)–(6) use an entropy-balanced sample following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	S	Standard Samp	ple	Entro	py-Balanced	Sample
	2000-2009	2010-2018	All Years	2000–2009	2010-2018	All Years
	(1)	(2)	(3)	(4)	(5)	(6)
Gender-Diverse	0.250	8.623**	1.603	0.899	8.623**	2.435
	(0.112)	(2.590)	(0.771)	(0.424)	(2.542)	(1.234)
Gender-Diverse $\times$ Post			8.413**			7.175**
			(2.371)			(2.048)
ln(Sales)	3.464	3.701	3.147	5.873	4.919	5.090
	(0.806)	(0.911)	(0.827)	(1.342)	(1.097)	(1.264)
Offer Price Revision	1.019***	0.335**	1.053***	0.572***	0.267*	0.597***
	(3.950)	(2.283)	(4.360)	(3.780)	(1.920)	(3.881)
ln(News)	0.783	2.106	0.103	0.390	1.939	-0.200
	(0.582)	(1.652)	(0.092)	(0.303)	(1.518)	(-0.185)
Total Debt / Assets	-7.555	-11.435	-8.318*	-14.531	-12.737	-14.507**
	(-1.299)	(-1.207)	(-1.777)	(-1.641)	(-1.379)	(-2.114)
IB Market Share	-4.634	-6.076	-3.640	-3.661	-7.465	-2.317
	(-1.076)	(-0.876)	(-0.890)	(-0.941)	(-0.988)	(-0.591)
Avg. Underpricing $[-30,-1]$	-14.541	-7.847	-12.882	-3.040	-4.811	2.593
	(-0.768)	(-0.609)	(-0.687)	(-0.203)	(-0.350)	(0.173)
Avg. Price Revision $[-30,-1]$	-2.017	2.370	0.630	2.642	0.573	1.042
	(-0.121)	(0.184)	(0.039)	(0.171)	(0.042)	(0.066)
Prior Market Return	-32.905	88.541	-58.543	-57.851	98.235	-78.940
	(-0.372)	(1.210)	(-0.793)	(-0.594)	(1.179)	(-1.043)
ln(Ret / Off)	-9.484	4.560	-8.710	-9.362	3.961	-7.868
	(-1.340)	(1.009)	(-1.322)	(-1.224)	(0.874)	(-1.257)
Offer Revision Flag	-116.364**	-12.133	-123.432***	-87.816**	-11.411	-102.400***
	(-2.508)	(-0.601)	(-2.759)	(-2.128)	(-0.572)	(-2.828)
ln(Industry Mkt / Sales)	0.427	2.142**	0.262	-1.421	2.225*	-1.016
	(0.144)	(2.102)	(0.104)	(-0.638)	(1.937)	(-0.512)
ln(Offer Cap. / Sales)	3.742	3.778	3.875	5.424	4.770	5.410
	(0.964)	(0.968)	(1.097)	(1.502)	(1.113)	(1.547)
Avg. Industry Ret. $[-30,-1]$	-6.553	3.778	-4.206	-3.654	1.796	-2.481
	(-1.295)	(0.490)	(-0.934)	(-0.767)	(0.232)	(-0.570)
Std. Industry Ret. $[-30,-1]$	3.121	-0.817	2.367	1.131	-1.320	0.944
	(1.611)	(-0.225)	(1.111)	(0.581)	(-0.332)	(0.448)
Avg. NASDAQ Ret. $[-30,-1]$	10.569	3.701	12.746	11.061	1.955	14.189
	(0.880)	(0.240)	(1.364)	(0.894)	(0.115)	(1.503)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Fully Saturated Model			$\checkmark$			$\checkmark$
Adj. R-Square	0.499	0.359	0.461	0.402	0.380	0.383
Observations	614	498	1,112	614	498	1,112

Table 3Effect on Underpricing Across Time

*Notes:* The dependent variable in all columns is an IPO's underpricing on the first trading date. The specifications in all columns include the controls and fixed effects used in Columns (3) and (6) of Table 2. We run separate regressions for IPOs in the 2000s in Columns (1) and (4) and for IPOs in the 2010s in Columns (2) and (5). In Columns (3) and (6), we interact *Post*, which equals one for IPOs in the 2010s and zero otherwise, with the focal regressor, *Gender-Diverse*. The models used in Columns (3) and (6) incorporate a fully saturated set of controls, including interaction terms between each control and the *Post* indicator. Columns (4)–(6) use an entropy-balanced sample following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	2000-2009	2010-2018	All Years	2000-2009	2010-2018	All Years
	(1)	(2)	(3)	(4)	(5)	(6)
Gender-Diverse $\times$ Large Trades	-6.822**	7.032**	-6.857**			
2	(-1.993)	(2.391)	(-2.304)			
Large Trades	-6.384*	-10.918***	-5.540**			
-	(-1.890)	(-3.912)	(-1.988)			
Gender-Diverse $\times$ Large Trades $\times$ Post			14.951***			
2			(3.606)			
Gender-Diverse $\times$ Small Trades				-0.004	-0.005	-0.005
				(-0.083)	(-0.548)	(-0.122)
Small Trades				0.064*	0.017	0.060*
				(1.809)	(1.642)	(1.716)
Gender-Diverse $\times$ Small Trades $\times$ Post						0.001
						(0.031)
Gender-Diverse	6.364*	6.636*	7.916**	1.474	10.063***	2.707
	(1.699)	(1.853)	(2.524)	(0.436)	(2.670)	(0.888)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.424	0.389	0.400	0.412	0.396	0.399
Observations	614	498	1,112	614	498	1,112

## Table 4 Which Investors Drive the Underpricing Effect?

*Notes:* This table reports estimations of the effect that institutional and retail trading have, individually, on the gender diversity underpricing effect. The dependent variable in all columns is an IPO's underpricing on the first trading date. The columns mimic those used in Table 3, where we run separate regressions for IPOs in the 2000s and again for IPOs in the 2010s, and then we interact *Post* with *Gender-Diverse*. The controls used in each column also mirror those in the corresponding columns of Table 3. In Columns (1)–(3), we interact into the models *Large Trades*, which equals the number of block trades of 10,000 shares or more made on the first trading date. In Columns (4)–(6), we interact into the models *Small Trades*, which equals the number of small trades of 1,000 shares or less made on the first trading date. We use an entropy-balanced sample in all columns, following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	Per	rcent Inst. Ow	'n	Percent Big Three Own			
	2000-2009	2010-2018	All Years	2000-2009	2010-2018	All Years	
	(1)	(2)	(3)	(4)	(5)	(6)	
Gender-Diverse	-0.035	0.054*	-0.053**	-0.002***	0.006	-0.002	
	(-1.547)	(1.783)	(-2.201)	(-3.338)	(1.326)	(-1.341)	
Gender-Diverse $\times$ Post			0.116***			0.007*	
			(3.238)			(1.758)	
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$		
Con. Col. (3) & (6), Table 3			$\checkmark$			$\checkmark$	
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
Adj. R-Square	0.228	0.445	0.418	0.186	0.216	0.331	
Observations	554	492	1,046	554	492	1,046	

Table 5
Changes in Post-IPO Institutional Ownership Across Time

*Notes:* This table reports estimations of the effect of board gender diversity on the institutional ownership of the firm's shares. The dependent variable in Columns (1)–(3) is *Percent Inst. Own*, the fraction of shares owned by institutional investors based on the first ownership report after the IPO. The dependent variable in Columns (4)–(6) is *Percent Big Three Own*, the fraction of shares owned by either BlackRock, State Street, or Vanguard based on the first ownership report after the IPO. The columns mimic those used in Table 3, where we run separate regressions for IPOs in the 2000s and again for IPOs in the 2010s, and then we interact *Post* with *Gender-Diverse*. The controls used in each column also mirror those in the corresponding columns of Table 3. We use an entropy-balanced sample in all columns, following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

Table 6
Effect of Board Gender Diversity on Other IPO Outcomes

	Full Sample	2000-2009	2010-2018	Full Sample
	(1)	(2)	(3)	(4)
Gender-Diverse	0.091	0.436	0.059	0.462
	(0.285)	(1.241)	(0.114)	(1.273)
Gender-Diverse $\times$ Post				-0.390
				(-0.621)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3				$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.300	0.432	0.170	0.303
Observations	1,112	614	498	1,112

#### Panel A: Mid-point of Initial File Price Range

#### **Panel B: Offer Price Change**

	Full Sample	2000–2009	2010-2018	Full Sample
	(1)	(2)	(3)	(4)
Gender-Diverse	0.105	0.653	0.345	0.743
	(0.105)	(0.426)	(0.232)	(0.509)
Gender-Diverse $\times$ Post				0.289
				(0.139)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3				$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.613	0.574	0.680	0.627
Observations	1,112	614	498	1,112

#### Panel C: Final Offer Price at Date of IPO

	Full Sample	2000-2009	2010-2018	Full Sample
	(1)	(2)	(3)	(4)
Gender-Diverse	0.195	0.531	0.220	0.614
	(0.529)	(1.409)	(0.348)	(1.539)
Gender-Diverse $\times$ Post				-0.277
				(-0.365)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3				$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.443	0.604	0.324	0.452
Observations	1,112	614	498	1,112

*Notes:* The dependent variable in Panel A is the mid-point of the initial file price range. The dependent variable in Panel B is the percent change in price from the initial file price to the final offer price, and the dependent variable in Panel C is the final offer price. Column (1) uses the full sample of IPOs across all years and includes the full set of control variables and fixed effects. Columns (2)–(4) mimic those used in Table 3, where we run separate regressions for IPOs in the 2000s and again for IPOs in the 2010s, and then we interact *Post* with *Gender-Diverse*. The controls used in each column also mirror those in the corresponding columns of Table 3. We use an entropy-balanced sample in all columns, following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Impact of Underwriter Network Centrality on Underpricing Effect						
$\begin{array}{cccccccc} (-2.279) \\ \text{Gender-Diverse} \times \text{Post} & 16.250^{***} \\ (3.011) \\ \text{High Centrality} \times \text{Post} & 5.970 \\ (0.871) \\ \text{Gender-Diverse} \times \text{High Centrality} \times (2010-2013) & -6.103 \\ (-0.759) \\ \text{Gender-Diverse} \times (2010-2013) & 14.283^{**} \\ (2.266) \\ \text{High Centrality} \times (2010-2013) & 5.521 \\ (0.802) \\ \text{Gender-Diverse} \times \text{High Centrality} \times (2014-2018) & -22.351^{**} \\ (-2.430) \\ \text{Gender-Diverse} \times (2014-2018) & 20.677^{**} \\ (2.586) \\ \text{High Centrality} \times (2014-2018) & 4.070 \\ (0.442) \\ \text{Gender-Diverse} \times \text{High Centrality} & 6.844 & 6.649 \\ (1.484) & (1.443) \\ \text{Gender-Diverse} & -1.116 & -0.999 \\ (-0.348) & (-0.313) \\ \text{High Centrality} & -6.161 & -5.954 \\ (-1.191) & (-1.145) \\ \text{Con. Col. (3) & (6), Table 3} & \checkmark & \checkmark \\ \text{Entropy-Balanced Sample} & \checkmark & \checkmark \\ \text{Adj. R-Square} & 0.384 & 0.385 \\ \end{array}$		(1)	(2)				
Gender-Diverse × Post16.250*** (3.011)High Centrality × Post5.970 (0.871)Gender-Diverse × High Centrality × (2010–2013)-6.103 (-0.759)Gender-Diverse × (2010–2013)14.283** (2.266)High Centrality × (2010–2013)5.521 (0.802)Gender-Diverse × High Centrality × (2014–2018)-22.351** (-2.430)Gender-Diverse × (2014–2018)20.677** (2.586)High Centrality × (2014–2018)4.070 (0.442)Gender-Diverse × High Centrality6.844 (1.484)Gender-Diverse × High Centrality6.844 (0.442)Gender-Diverse × High Centrality6.844 (1.484)Gender-Diverse × High Centrality6.844 (1.484)Gender-Diverse-1.116 (-0.999) (-0.348)Gender-Diverse-1.116 (-0.999) (-0.348)Gender-Diverse-1.116 (-0.145)Con. Col. (3) & (6), Table 3 Entropy-Balanced Sample $\checkmark$ $\checkmark$ Adj. R-SquareAdj. R-Square0.384 (0.385)	Gender-Diverse $\times$ High Centrality $\times$ Post	-14.865**					
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		· ,					
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Entropy-Balanced Sample✓Adj. R-Square0.3840.385	Con. Col. (3) & (6). Table 3						
Adj. R-Square         0.384         0.385							
J 1		0.384	0.385				
Observations 1,112 1,112	Observations	1,112	1,112				

 Table 7

 Impact of Underwriter Network Centrality on Underpricing Effect

*Notes:* This table reports estimates of the interactive effect on underpricing of board gender diversity and underwriter network centrality. The dependent variable in all specifications is an IPO's underpricing on the first trading date. For each IPO, we identify the average value of *Degree* across its underwriters and we create an indicator variable, *High Centrality*, that equals one if this average value of *Degree* is above the sample median, and zero otherwise. *Post* equals one for IPOs conducted in the 2010s, and zero otherwise. (2010-2013) equals one for IPOs conducted in the 2010–2013 period, and zero otherwise, and (2014-2018) equals one for IPOs conducted in the 2014–2018 period, and zero otherwise. We include all controls and fixed effects from Columns (3) and (6) of Table 2. We use an entropy-balanced sample in all columns, following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

8	2000 2000	2010 2019	A 11 X/2 2 112
	2000-2009	2010-2018	All Years
	(1)	(2)	(3)
Gender-Diverse	0.160	0.053	0.100
	(1.185)	(0.695)	(0.833)
Gender-Diverse $\times$ Post			-0.065
			(-0.454)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.101	0.775	0.471
Observations	607	494	1,101

Table 8
Effect of Board Gender Diversity on Future Performance
Panel A: Accounting Performance

#### **Panel B: Accounting Restatements**

	2000-2009	2010-2018	All Years
	(1)	(2)	(3)
Gender-Diverse	0.029	-0.051	0.054
	(0.575)	(-0.763)	(1.153)
Gender-Diverse $\times$ Post			-0.087
			(-1.236)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.164	0.122	0.153
Observations	614	498	1,112

Panel C: Lawsuits			
	2000-2009	2010-2018	All Years
	(1)	(2)	(3)
Gender-Diverse	-0.005	-0.058	0.029
	(-0.049)	(-0.514)	(0.318)
Gender-Diverse $\times$ Post			-0.076
			(-0.569)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.057	0.189	0.148
Observations	614	498	1,112

*Notes:* The dependent variable in Panel A is the firm's industry- and size-adjusted return on assets in the year following the IPO. The dependent variable in Panel B is the number of accounting restatements incurred by the firm in the five years after IPO, and the dependent variable in Panel C is the number of lawsuits involving the firm in the five years after IPO. The columns mimic those used in Table 3, where we run separate regressions for IPOs in the 2000s and again for IPOs in the 2010s, and then we interact *Post* with *Gender-Diverse*. The controls used in each column also mirror those in the corresponding columns of Table 3. We use an entropy-balanced sample in all columns, following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

	2000-2009	2010-2018	All Years
	(1)	(2)	(3)
Gender-Diverse	-1.850	-0.595	-0.857
	(-1.538)	(-0.460)	(-0.747)
Gender-Diverse $\times$ Post			-0.346
			(-0.215)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.119	0.028	0.077
Observations	613	495	1,108

# Table 9 Effect of Board Gender Diversity on Post-IPO Market Efficiency Panel A: 5-Day Post-IPO Buy-and-Hold Abnormal Returns

#### Panel B: 10-Day Post-IPO Buy-and-Hold Abnormal Returns

	2000-2009	2010-2018	All Years
	(1)	(2)	(3)
Gender-Diverse	-1.364	-1.471	-0.030
	(-0.946)	(-0.815)	(-0.020)
Gender-Diverse $\times$ Post			-1.706
			(-0.820)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.100	0.045	0.059
Observations	613	495	1,108

#### Panel C: 25-Day Post-IPO Buy-and-Hold Abnormal Returns

	2000-2009	2010-2018	All Years
	(1)	(2)	(3)
Gender-Diverse	-3.001	-1.998	-1.786
	(-1.483)	(-0.813)	(-1.000)
Gender-Diverse $\times$ Post			0.082
			(0.031)
Con. Col. (3) & (6), Table 2	$\checkmark$	$\checkmark$	
Con. Col. (3) & (6), Table 3			$\checkmark$
Entropy-Balanced Sample	$\checkmark$	$\checkmark$	$\checkmark$
Adj. R-Square	0.094	0.075	0.112
Observations	613	495	1,108

*Notes:* The dependent variable in Panels A, B, and C is the firm's 5-day, 10-day, and 25-day buy-and-hold abnormal return following the IPO date, respectively. The columns mimic those used in Table 3, where we run separate regressions for IPOs in the 2000s and again for IPOs in the 2010s, and then we interact *Post* with *Gender-Diverse*. The controls used in each column also mirror those in the corresponding columns of Table 3. We use an entropy-balanced sample in all columns, following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

### A. Appendix

Variable Definitions

Variable Definitions		
Variable	Definition	Source
Main Regressor and Outcomes		V D.
Gender-Diverse	This equals one if there is at least one woman on the board, and zero otherwise.	Kenney-Patton
Underpricing	The percentage change in the price of a share of stock on the first trading date of the IPO	Thomson One/SD
Unrealized Proceeds	from offer to close. The price change from the offer price to the closing first-day market price, multiplied by the number of shares issued (in \$ millions).	Thomson One/SD
Offer Price	The final offer price of the IPO.	Thomson One/SD
Mid-Point of Initial File Price	The initial file price of the IPO, or the mid-point between the low price and the high price	Thomson One/SD
Range	of the initial file price range.	Thomson One/SD
Main Controls		
In(Sales)	Equal to the natural logarithm of the firm's sales.	Compustat
Offer Price Change	We follow Hanley (1993) and measure this as the percent difference between the expected offer price and the actual offer price, where the expected offer price is equal to the average	Thomson One/SD
	of the highest and lowest prices in the original file price range.	
ln(News)	Equal to the natural log of one plus the number of unique new articles published about the company in the six months prior to the IPO. We begin with the values provided by Butler et al. (2014), and then we fill in missing observations using a query of Google	Google News
	News archives.	0
Total Debt / Assets IB Market Share	Long-term debt plus debt in current liabilities divided by assets. This equals the ratio between the proceeds that went to lead investment bank and the total	Compustat Thomson One/SD
	proceeds from the IPO (sum of all markets).	
Avg. Underpricing $[-30, -1]$	The average IPO first trading day return in the 30 days prior to the IPO issue date.	Thomson One/SD
Avg. Price Revision <sub>[-30,-1]</sub> Prior Market Return	The average <i>Offer Price Change</i> of IPOs in the 30 days prior to the IPO issue date.	Thomson One/SD
Prior Market Return	Buy-and-hold return of the equal-weighted CRSP market index in the three weeks leading up to the IPO date using daily data. Our results are very similar if we instead use the value-weighted CRSP market index.	CRSP
n(Ret / Off)	Equal to the natural log of one plus the number of secondary shares retained divided by the total number of shares offered (sum of all markets).	Thomson One/SD
Offer Revision Flag	Equals the <i>Offer Price Change</i> if the <i>Offer Price Change</i> < 0; otherwise it equals zero.	Thomson One/SD
ln(Industry Mkt / Sales)	The rolling 12-month average of the industry market value to sales ratio where market value is equal to the firm's first closing share price multiplied by the number of shares of stock outstanding. IPOs are assigned to one of the 49 Fama-French industries using SIC codes.	Compustat
In(Offer Cap. / Sales)	The natural log of the offer price times the number of shares outstanding, divided the annual value of firm sales.	Thomson One/SD
Avg. Industry $Return_{[-30,-1]}$	The average return in a given industry in the 30 days prior to the IPO issue date based on Fama-French industry returns. IPOs are assigned to one of the 49 Fama-French industries using SIC codes.	Ken French Websi
Std. Industry $Return_{[-30,-1]}$	The standard deviation of the returns in a given industry in the 30 days prior to the IPO issue date based on Fama-French industry returns. IPOs are assigned to one of the 49	Ken French Webs
Avg. NASDAQ Return <sub>[-30,-1]</sub>	Fama-French industries using SIC codes. The average NASDAQ composite return in the 30 days prior to the IPO issue date.	CRSP
Additional Controls		
n(Assets)	Equal to the natural logarithm of the firm's assets.	Compustat
n(Firm Age)	Equal to the natural log of one plus the age of the firm in years (i.e., the number of years between the issue date and the founding date).	Jay Ritter's Websi
Гор-Tier Underwriter	Equal to one if the lead underwriter is either Goldman Sachs, Morgan Stanley, or JP Morgan, and zero otherwise. This designation is motivated by materials on Jay Ritter's website.	Thomson One/SD
Share Overhang	Our overhang variable is the same as that in Bradley and Jordan (2002), which equals the ratio of retained shares to the public float (i.e., retained shares to issued shares).	Thomson One/SD
VC Dummy	Equal to one if the firm has venture capital funding, and zero otherwise. From Jay Ritter's November 16th, 2020 IPO database.	Jay Ritter's Websi
Internet Dummy	Equal to one if the firm is an internet-based company, and zero otherwise. From Jay Ritter's November 16th, 2020 IPO database.	Jay Ritter's Websi
Tech Dummy	Following Loughran and Ritter (2004), equal to one if the firm's SIC code is one of the following: 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371, 7372, 7373, 7374, 7375, 7378, 7379, and zero otherwise.	CRSP
NASDAQ Dummy	Equal to one if the IPO is listed on NASDAQ as defined by a CRSP exchange code equal to 3, and zero otherwise.	CRSP

Market Capitalization	Equal to the firm's first closing share price multiplied by the number of shares of stock outstanding. For firms with dual-class shares, we use data on the number of shares outstanding in Thomson One.	Thomson One/SDC
Female CEO	Equal to one if a woman is the CEO of the firm, and zero otherwise.	Kenney-Patton
Std. Underpricing $[-30,-1]$	The standard deviation of the IPO first trading day returns in the 30 days prior to the IPO	Thomson One/SDC
Sta: Onderprieng[=30,=1]	issue date.	
Std. Drive Devision		Thomson One/SDC
Std. Price Revision $[-30,-1]$	The standard deviation of the Offer Price Changes of IPOs in 30 days prior to the IPO	Thomson One/SDC
	issue date.	
Std. NASDAQ Return <sub>[-30,-1]</sub>	The standard deviations of the NASDAQ composite returns in the 30 days prior to the	CRSP
	IPO issue date based on Fama-French industry returns.	
ln(Off / Out)	Equal to the natural log of one plus the number of secondary shares offered divided by	Thomson One/SDC
× /	the total number of shares outstanding.	
Amended Offer Revision	The percent difference between the amended offer price and the actual offer price, where	Thomson One/SDC
Amended Offer Revision	the amended offer price is equal to the average of the highest and lowest prices in the	Thomson One/SDC
	amended file price range.	
Selling Fee / Proceeds	Equal to the total selling concession divided by the total proceeds of the IPO.	Thomson One/SDC
Pure Primary Dummy	Equal to one if the SDC variable "prim shs as % of shs ofrd - sum of all mkts" equals	Thomson One/SDC
	100, and zero otherwise.	
Centrality and Ownership Var	iables	
Degree	The Degree measure used in Bajo et al. (2016). For each IPO, we consider each un-	Thomson One
Degree	derwriter of the deal. We then look back five years (including the year of the IPO) and	Thomson One
	identify how many unique IPO underwriters exist in the sample $(N)$ . We then note how	
	many unique underwriters the focal underwriter was connected to by being part of the	
	same syndicate of underwriters on IPOs in that five-year period. This value becomes n.	
	For a given underwriter-year, the <i>Degree</i> measure equals <i>n</i> / <i>N</i> .	
Avg. Underwriter Centrality	For each IPO, we identify the value of <i>Degree</i> of each of its underwriters and take the	Thomson One
· 3· · · · · · · · · · · · · · · · · ·	average.	
Lead Underwriter Centrality	For each IPO, we identify the value of <i>Degree</i> of its lead underwriter.	Thomson One
		Thomson One
High Centrality	Equal to one if Avg. Underwriter Centrality is above the sample median, and zero other-	Thomson One
D I I I	wise.	
Percent Inst. Own	Equal to the fraction of a firm's shares owned by institutional investors in the first owner-	Thomson Reuters
	ship report after the firm's IPO.	
Percent Big Three Own	Equal to the fraction of a firm's shares owned by either BlackRock, State Street, or Van-	Thomson Reuters
	guard in the first ownership report after the firm's IPO.	
Financial and CSR Controls		
Operating CF / CAPEX	Cash flow income before extraordinary items divided by capital expenditures.	Compustat
Operating ROA	Operating income after depreciation divided by lagged assets.	Compustat
1 0		
R&D / Assets	Research and development expenditures divided by assets.	Compustat
R&D / Assets PPE / Assets	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets.	Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets.	Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities.	Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets.	Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities.	Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities.	Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities.	Compustat Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research &	Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility	Compustat Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two	Compustat Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility	Compustat Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two	Compustat Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b>	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.	Compustat Compustat Compustat Compustat Compustat Compustat KLD
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.	Compustat Compustat Compustat Compustat Compustat Compustat
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b>	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.	Compustat Compustat Compustat Compustat Compustat Compustat KLD
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years. Equal to the number of female directors on the board divided by the board size. The average age of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren	Compustat Compustat Compustat Compustat Compustat Compustat KLD
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years. Equal to the number of female directors on the board divided by the board size. The average age of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age	<ul> <li>Research and development expenditures divided by assets.</li> <li>Total net property, plant, and equipment divided by assets.</li> <li>Long-term debt divided by assets.</li> <li>Long-term debt divided by the difference between current assets and current liabilities.</li> <li>Current assets divided by current liabilities.</li> <li>Current assets minus inventories, divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research &amp; Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.</li> <li>Equal to the number of female directors on the board divided by the board size.</li> <li>The average age of the directors on the board in a given year.</li> <li>We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of</li> </ul>	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age	<ul> <li>Research and development expenditures divided by assets.</li> <li>Total net property, plant, and equipment divided by assets.</li> <li>Long-term debt divided by assets.</li> <li>Long-term debt divided by the difference between current assets and current liabilities.</li> <li>Current assets divided by current liabilities.</li> <li>Current assets minus inventories, divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research &amp; Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.</li> <li>Equal to the number of female directors on the board divided by the board size.</li> <li>The average age of the directors on the board in a given year.</li> <li>We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average</li> </ul>	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age Avg. Director Skills	<ul> <li>Research and development expenditures divided by assets.</li> <li>Total net property, plant, and equipment divided by assets.</li> <li>Long-term debt divided by assets.</li> <li>Long-term debt divided by the difference between current assets and current liabilities.</li> <li>Current assets divided by current liabilities.</li> <li>Current assets minus inventories, divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research &amp; Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.</li> <li>Equal to the number of female directors on the board divided by the board size.</li> <li>The average age of the directors on the board in a given year.</li> <li>We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year.</li> </ul>	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age	<ul> <li>Research and development expenditures divided by assets.</li> <li>Total net property, plant, and equipment divided by assets.</li> <li>Long-term debt divided by assets.</li> <li>Long-term debt divided by the difference between current assets and current liabilities.</li> <li>Current assets divided by current liabilities.</li> <li>Current assets minus inventories, divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research &amp; Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.</li> <li>Equal to the number of female directors on the board divided by the board size.</li> <li>The average age of the directors on the board in a given year.</li> <li>We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year.</li> </ul>	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age Avg. Director Skills	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years. Equal to the number of female directors on the board divided by the board size. The average age of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year. The average number of characters, including spaces, in the directors' IPO prospectus biographies for the directors on the board in a given year.	Compustat Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age Avg. Director Skills	<ul> <li>Research and development expenditures divided by assets.</li> <li>Total net property, plant, and equipment divided by assets.</li> <li>Long-term debt divided by assets.</li> <li>Long-term debt divided by the difference between current assets and current liabilities.</li> <li>Current assets divided by current liabilities.</li> <li>Current assets minus inventories, divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>Cash and short-term investments divided by current liabilities.</li> <li>We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research &amp; Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years.</li> <li>Equal to the number of female directors on the board divided by the board size.</li> <li>The average age of the directors on the board in a given year.</li> <li>We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year.</li> </ul>	Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age Avg. Director Skills	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years. Equal to the number of female directors on the board divided by the board size. The average age of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year. The average number of characters, including spaces, in the directors' IPO prospectus biographies for the directors on the board in a given year.	Compustat Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score Director Characteristics Fraction Female Avg. Director Age Avg. Director Skills Avg. Director Bio. Length Avg. Directors with Doctorate	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years. Equal to the number of female directors on the board divided by the board size. The average age of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year. The average number of characters, including spaces, in the directors' IPO prospectus biographies for the directors on the board in a given year. The number of directors on the board with a Doctorate degree, divided by the total number of directors on the board.	Compustat Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton Kenney-Patton Kenney-Patton
R&D / Assets PPE / Assets Debt / EBITDA Debt / NWC Current Ratio Quick Ratio Cash Ratio CSR Score <b>Director Characteristics</b> Fraction Female Avg. Director Age Avg. Director Skills	Research and development expenditures divided by assets. Total net property, plant, and equipment divided by assets. Long-term debt divided by assets. Long-term debt divided by the difference between current assets and current liabilities. Current assets divided by current liabilities. Current assets minus inventories, divided by current liabilities. Cash and short-term investments divided by current liabilities. Cash and short-term investments divided by current liabilities. We compile firm-year CSR scores using the Kinder, Lydenberg, and Domini Research & Analytics (KLD) data. To capture a firm's average level of corporate social responsibility post-IPO, we take the average of the firm's CSR score in the year of its IPO and the two subsequent years. Equal to the number of female directors on the board divided by the board size. The average age of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then consider the average number of skills possessed by the directors on the board in a given year. The average number of characters, including spaces, in the directors' IPO prospectus biographies for the directors on the board in a given year.	Compustat Compustat Compustat Compustat Compustat Compustat Compustat KLD Kenney-Patton Kenney-Patton Kenney-Patton

Avg. Ethnicity <sub>i</sub>	Number of directors on the board in ethnic group <i>i</i> , divided by the total number of directors on the board. We classify directors in one of thirteen different ethnic groups based on the ethnic encoding process of List Service Direct, which uses directors' first, middle,	List Service Direct
Avg. Religion <sub>i</sub>	and last names to determine the most likely ethnicity of the director. Number of directors on the board in religious group <i>i</i> , divided by the total number of directors on the board. We classify directors in one of eleven different religious groups based on the ethnic encoding process of List Service Direct, which uses directors' first, middle, and last names to determine the most likely religion of the director.	List Service Direct
Avg. Language <sub>i</sub>	Number of directors on the board in primary-language group <i>i</i> , divided by the total number of directors on the board. We classify directors in one of thirty-four different primary-language groups based on the ethnic encoding process of List Service Direct, which uses directors' first, middle, and last names to determine the most likely primary-language of the director.	List Service Direct
Std. Director Age Std. Director Skills	The standard deviation of the ages of the directors on the board in a given year. We identify director skillsets using the taxonomy of Adams, Akyol, and Verwijmeren (2018) and by searching the prospectus biographies for the strings listed therein. The authors identify twenty different skills commonly held by directors, so our number of skills variable takes on discrete values from zero to twenty. We then take the standard deviation of the number of skills possessed by the directors on the board in a given year.	Kenney-Patton Kenney-Patton
Std. Director Bio. Length	The standard deviation of the number of characters, including spaces, in the directors' IPO prospectus biographies for the directors on the board in a given year.	Kenney-Patton
Std. Directors with Doctorate Std. Directors with Master's Std. Ethnicity	The standard deviation of the number of directors on the board with a Doctorate degree. The standard deviation of the number of directors on the board with a Master's degree. The standard deviation of the ethnicities of the directors, where directors are classified into one of thirteen different ethnic groups based on the ethnic encoding process of List Service Direct, which uses directors' first, middle, and last names to determine the most	Kenney-Patton Kenney-Patton List Service Direct
Std. Religion	likely ethnicity of the director. The standard deviation of the religions of the directors, where directors are classified into one of eleven different religious groups based on the ethnic encoding process of List Service Direct, which uses directors' first, middle, and last names to determine the most likely religion of the director.	List Service Direct
Std. Language	The standard deviation of the ethnicities of the directors, where directors are classified into one of thirty-four different primary-language groups based on the ethnic encoding process of List Service Direct, which uses directors' first, middle, and last names to determine the most likely primary-language of the director.	List Service Direct
Other Variables		
Post	Equal to one if the IPO issue date is on or after January 1st, 2010, and zero otherwise.	Thomson One/SDC
Large Trades	Equal to the number of trades of 10,000 shares or more, made on the first trading date.	TAQ
Small Trades Return on Assets	Equal to the number of trades of less than 1,000 shares, made on the first trading date. Industry- and size-adjusted income before extraordinary items divided by total assets at the start of the year.	TAQ Compustat
Number of Future Restate-	For each IPO in our sample, we sum up the number of accounting restatements incurred	Audit Analytics
ments Number of Future Lawsuits	by the firm in the five years after IPO. For each IPO in our sample, we sum up the number of instances in which the firm was named as a defendant in a class action lawsuit in the five years after IPO.	Audit Analytics
n-Day Post-IPO BHAR	Buy-and-hold daily returns over <i>n</i> days (i.e., the product of one plus the daily return) less the return on the value-weighted CRSP market index over the same time period.	CRSP
Industry	Based on two-digit SIC code classifications.	Compustat

	S	tandard Samp	le	Entrop	y-Balanced S	ample
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction Female	23.827***	29.579***	32.082***	23.569***	29.257***	31.308***
	(3.450)	(3.415)	(3.490)	(3.318)	(3.320)	(3.298)
ln(Sales)	0.572	5.384*	5.257*	1.459	5.325**	5.363**
	(0.530)	(1.850)	(1.859)	(1.258)	(1.983)	(2.046)
Offer Price Revision	0.876***	0.868***	0.847***	0.670***	0.591***	0.572***
	(5.080)	(3.798)	(3.672)	(6.516)	(4.339)	(4.175)
ln(News)	0.826	0.561	0.656	0.564	0.493	0.546
	(1.182)	(0.750)	(0.848)	(0.764)	(0.628)	(0.676)
Total Debt / Assets	-6.720*	-4.771	-4.524	-9.750**	-7.113	-7.454
	(-1.807)	(-1.152)	(-1.114)	(-2.294)	(-1.459)	(-1.524)
IB Market Share	-2.152	-3.570	-4.055	-1.705	-3.182	-3.273
	(-0.826)	(-1.147)	(-1.291)	(-0.659)	(-1.080)	(-1.090)
Avg. Underpricing $[-30,-1]$	-10.230	-20.689	-19.880*	-5.216	-14.233	-14.640
L / J	(-1.225)	(-1.642)	(-1.674)	(-0.704)	(-1.211)	(-1.292)
Avg. Price Revision $[-30,-1]$	-0.755	7.137	7.156	0.804	6.051	7.461
	(-0.071)	(0.590)	(0.618)	(0.083)	(0.557)	(0.703)
Prior Market Return	11.287	-3.407	-4.403	14.564	8.123	5.066
	(0.274)	(-0.070)	(-0.092)	(0.323)	(0.154)	(0.098)
ln(Ret / Off)	2.995	-3.775	-4.299	3.395	-0.561	-1.130
	(1.169)	(-0.616)	(-0.706)	(1.434)	(-0.108)	(-0.221)
Offer Revision Flag	-68.258***	-83.572***	-80.333***	-60.872***	-67.558***	-61.105**
	(-3.257)	(-3.016)	(-2.813)	(-3.470)	(-2.651)	(-2.546)
ln(Industry Mkt / Sales)	0.623	0.728	0.406	0.919	1.236	0.919
	(0.824)	(0.951)	(0.483)	(1.227)	(1.624)	(1.085)
ln(Offer Cap. / Sales)	1.052	5.556**	5.789**	1.519	5.141**	5.426**
	(0.871)	(2.147)	(2.203)	(1.310)	(2.163)	(2.283)
Avg. Industry $\operatorname{Ret}_{[-30,-1]}$	-3.630	-1.926	-2.111	-2.564	-0.216	-0.650
	(-0.996)	(-0.500)	(-0.562)	(-0.674)	(-0.058)	(-0.175)
Std. Industry Ret. $[-30,-1]$	2.022	0.595	0.499	1.272	0.720	0.315
	(1.030)	(0.352)	(0.281)	(0.760)	(0.450)	(0.191)
Avg. NASDAQ Ret. $[-30,-1]$	13.366**	14.610*	14.476**	14.061*	13.498	13.454*
- [ 20, -]	(2.345)	(1.917)	(2.060)	(1.885)	(1.606)	(1.731)
Year & Industry Fixed Effects	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Director Characteristic Con.		$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$
Loughran and Ritter (2004) Con.		$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$
Glushkov et al. (2018) Con.			$\checkmark$			$\checkmark$
Adj. R-Square	0.421	0.436	0.434	0.356	0.375	0.375
Observations	1,112	1,112	1,112	1,112	1,112	1,112

 Table A.1

 Effect of Increased Female Director Representation on IPO Underpricing

*Notes:* The dependent variable in all columns is an IPO's underpricing on the first trading date. The focal regressor is the variable *Fraction Female*. We control for the 15 main determinants of underpricing mentioned by Butler et al. (2014), year fixed effects, and industry fixed effects in all columns. In Columns (2) and (5) we also control for 33 additional determinants of underpricing, director characteristics, and firm characteristics, including those mentioned by Loughran and Ritter (2004), along with 13 ethnic group controls, 11 religious group controls, and 34 primary-language group controls. In Columns (3) and (6) we include 9 financial controls mentioned by Glushkov et al. (2018). Columns (4)–(6) use an entropy-balanced sample following the procedure in Hainmueller (2012). Standard errors are clustered by industry-year, using two-digit SIC code industry classifications. *t*-statistics are reported in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix.

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