Board Diversity and Innovative Efficiency in IPO Firms

Ruth O. Sagay[1*], Marc Goergen[3,4], Svetlana Mira[2], Onur Kemal Tosun[2]

[1] School of Management, Swansea University, Swansea, United Kingdom
[2] Cardiff Business School, Cardiff University, Cardiff, United Kingdom
[3] IE Business School, IE University, Madrid, Spain
[4] European Corporate Governance Institute (ECGI), Brussels, Belgium

ABSTRACT

We investigate whether board diversity, in terms of gender, age, and professional expertise, influences the innovative efficiency of IPO firms. Answering this question is important since innovation requires higher levels of risk, and greater resource commitments for IPO firms as such firms are relatively unknown to the stock market. Consistent with the diversity theory, which predicts that greater board diversity increases cognitive conflicts that impede board effectiveness, we provide first evidence that age diversity of executive directors on the board of IPO firms is detrimental to innovative efficiency. Our results are robust to alternative econometric specifications and alternative measures of innovative efficiency. Further, the quality of corporate governance has no moderating effect on the relationship between executive directors' age diversity and innovative efficiency. Regulators, shareholders, and market participants should be aware of the negative aspects of board age diversity in executive directors when it comes to innovation efficiency.

JEL Classification Codes: G30, G39, M14, O30

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[*]Corresponding author's email address: r.o.sagay@swansea.ac.uk; address: School of Management, Swansea University, Bay Campus, Swansea SA1 8EN, UK.

1. Introduction

Innovation, consisting of the exploration of new untested ideas or the improvement of existing products, has been identified as a key determinant of corporate competitiveness and growth. For initial public offerings (IPOs), the ability to compete effectively is imperative for firm performance post-IPO (Guo and Zhou 2016) and innovation plays a key role in gaining a competitive advantage. Hence, innovation is vital to the financial success of newly listed firms. In turn, the input of the board of directors at every stage of the innovative process is vital, as the board provides the necessary tacit knowledge and relevant information (Faleye et al. 2014).

Innovative efficiency, coined by Hirshleifer et al. (2013), relates to the firm's ability to convert innovative input into output. Innovative input is defined as research and development expenditure (R&D), while innovative output relates to the patents granted to the firm and the citations for such patents. This paper examines how board diversity influences the efficiency of this process in IPO firms. More specifically, prior literature for mature US-listed firms by Griffin et al. (2021) suggests that one aspect of boards, i.e., board diversity, improves innovative efficiency.[1] They argue that board diversity improves board effectiveness during the innovative process by enhancing the board's monitoring and advising functions. However, much less is known about whether this relationship also applies to IPO firms. We attempt to fill this gap by providing evidence on the impact of board diversity on the innovative efficiency for US IPO firms.

In contrast to most extant literature, we adopt a broader definition of board diversity, which encompasses gender, age, and professional expertise diversity. In a second instance, we also distinguish between board diversity for the executive directors and board diversity for the non-executive directors.

We draw on two theories to inform our two competing hypotheses, i.e., the resource dependency theory and the diversity theory.[2] The resource dependency theory (Pfeffer and Salancik 1978) informs the hypothesis on the positive impact of board diversity on innovative efficiency. Conversely, Forbes and Milliken's (1999) diversity theory forms the basis for the hypothesis on the negative effect of board diversity on innovative efficiency.

[1] Griffin et al. (2021) find that firms with greater gender diversity have higher innovative efficiency i.e., such firms are more likely to generate patents for each dollar of R&D expenditure.

[2] Pfeffer and Salancik's (1978) resource dependency theory advances the board as a crucial source of resources, as directors draw on their prior experience to influence corporate decision-making. According to the diversity theory of Forbes and Milliken (1999), increased diversity and the resulting increase in more diverse views may inhibit board effectiveness via greater cognitive conflicts in the boardroom.

We test our hypotheses using a random sample of 661 IPO firms, which represents 25% of the population of IPOs completed on the NASDAQ, NYSE, and AMEX between January 1st, 1997, and December 31st, 2015. We use a random sample given the time-intensive nature of hand collecting data for individual director on the board. Each IPO firm is tracked from the IPO year (year 0) up to five years after going public (year 5). Hence, our period of study effectively ends on December 31st, 2020. Our final and unique sample is comprised of 3,198 firm-year observations.

To empirically test whether the measures of board diversity influence the innovative efficiency of IPO firms, we must address potential endogeneity concerns. First, there may be unobservable factors, such as the firm's corporate culture, that influence innovative efficiency. Hence, we employ the fixed effects (FE) regression technique, which includes firm fixed effects that control for firm-specific unobservable heterogeneity, and year fixed effects accounting for macroeconomic factors. Second, prior research has shown that board diversity may be endogenous (Chen et al. 2018). For instance, directors with sought after characteristics, such as female directors, may self-select onto the boards of IPO firms that are more efficient in terms of innovation, reflecting the quality of such firms. Therefore, we apply entropy balancing (EB) coined by Hainmueller (2012) and re-estimate the fixed effects regressions for the balanced samples. This approach allows us to achieve covariate balance of firm observables between firms with diversity in the boardroom and those without. Subsequently, there should be no observable differences, except for the level of board diversity. As such, the identification strategy in this paper mitigates potential endogeneity concerns when revealing the nature of the relationship between board diversity and innovative efficiency in IPO firms.

We find the following. First, our results show that age diversity for executive directors is detrimental to the IPO firm's ability to convert innovative input into output. This finding suggests that greater age diversity for executive directors increases cognitive conflicts in the boardroom, which harms the efficiency of the innovative process. Second, we find that gender and professional expertise diversity on the board do not explain innovative efficiency in IPO firms and this is also the case when we distinguish between diversity of executive and non-executive directors. Finally, we test whether our results are impacted by the quality of corporate governance in IPO firms. We find that the result remains unaffected by the level of board independence, board connections or the presence of venture capitalist directors on the board. Thus, there is no difference between well governed or poorly governed IPO firms in terms of the impact of board diversity on innovative efficiency. This is unsurprising as Field et al. (2013) suggest that, for IPO firms, it is less about monitoring in the boardroom but rather about the quality of advice received from the board.

This paper makes the following three important contributions to extant IPO literature. First, to the best of our knowledge, it provides novel evidence on the detrimental effect of age diversity for executive directors on innovative efficiency in IPO firms. Second, contrary to prior literature on mature US-listed firms (Chen et al. 2018; An et al. 2021; Griffin et al. 2021)[3], which suggests that gender diversity improves innovative efficiency, we show that gender and professional diversity in IPO firms do not affect innovative efficiency. This conclusion holds when examining diversity for the entire board or separately for executive and non-executive directors. Finally, our results emphasize the importance of examining diversity separately for executive and non-executive directors on the board, specifically in terms of age, as this influences innovative efficiency. Overall, we show that age diversity of executive directors affects innovative efficiency in IPO firms and that the story for IPO firms is different compared to mature firms.

The remainder of this paper is structured as follows. Section 2 reviews prior literature and develops the hypotheses. Section 3 outlines the data sources, sample selection, and the methodology. The next section reports the results from the empirical analysis, while Section 5 contains the robustness tests and further analysis. Finally, Section 6 concludes.

2. Literature Review and Hypothesis Development

Boards provide advice on various issues, including strategies to enter new markets and compete effectively. The more information is available to the board on the attractiveness of a new market, the more innovation is perceived to be favorable (Gehrke and Firk 2019). More generally, the consensus for IPO firms is that they require more advice-oriented boards to explore new opportunities, including innovation (Boone et al. 2007; Field et al. 2013). Drawing on the resource dependency theory, we argue that board diversity allows for a broader range of unique perspectives, increased access to information, and better processing of the available information, resulting in a more thorough evaluation of innovation opportunities. As such, the more varied experience and knowledge available to the board due to its greater diversity improves the board's advising function. Importantly, better advice helps the top management develop effective strategies and make business choices that enhance the firm's competitive advantage, its long-term growth, and its success. In other words, greater board diversity in IPO firms will result in better advice being given by the board. The outcome of this will be an efficient innovative process that ensures R&D expenditure yields greater output (i.e., patents and patent citations).

[3] Chen et al. (2018) find that firms with female board representation obtain more patents and patent citations in mature listed firms. Similarly, An et al. (2021) link their board diversity index to better innovation.

A myriad of studies on mature, listed firms provides relatively consistent evidence of a positive relationship between board diversity and innovation. In detail, Chen et al. (2018) study the impact of board gender diversity on innovation and firm performance. They find that firms with greater female board representation spend more on R&D and generate more patents. Chen et al. (2018) explain their findings by the argument that female directors improve the board's monitoring of the management, thereby preventing managers from enjoying a quiet life and shying away from putting in the effort required for innovation. Similarly, Cumming and Leung (2021) show that board gender diversity facilitates innovation, i.e., patents granted, although this effect differs across industries. More specifically, they find that firms in male-dominated industries benefit more from gender diversity, while firms in high-technology industries benefit more from scientific professional expertise. An et al. (2021), using a multidimensional board diversity index find that firms with diverse boards generate more patents and patent citations.[4] Their findings suggest that board diversity improves not only the quantity of patents generated but also their quality as evidenced by greater blue skies innovation. At an international level, Griffin et al. (2021) suggest that firms with gender diverse boards are granted more patents.

A related literature focuses on the effect of innovative efficiency on firm outcomes. Again, innovative efficiency refers to the firm's ability to convert innovative input into output. Importantly, Hirshleifer et al. (2013) find that innovative efficiency has a positive impact on market value and firm performance, suggesting that innovative efficiency is beneficial for corporate outcomes. Building on these findings, two recent studies explore the impact of diversity of R&D employee teams (Xie et al. 2020) and board diversity (Griffin et al. 2021), respectively, on innovative efficiency. First, Xie et al. (2020) find that gender diversity within R&D teams improves the innovative efficiency of the firm. They explain their findings by arguing that females in R&D teams provide informational benefits through their distinct knowledge base, resulting in high quality innovation. This indicates that gender diversity within R&D teams improves access to resources and consequently enhances innovative efficiency. Second, Griffin et al. (2021) demonstrate a positive link between board gender diversity and innovative efficiency for firms from 45 countries. The authors find that firms with female board representation generate more patents for each dollar spent on research and development. In other words, greater board gender diversity leads to improved innovative efficiency. More specifically, Griffin et al. (2021) show that board diversity improves the resource base of the firm through more CEO incentives that reward long term success while accommodating short term failures, a more innovative corporate culture, and increased diversity among

[4] An et al.'s (2021) board diversity index measures demographic diversity, director experience diversity, managerial trait diversity, cultural diversity, professional diversity, and educational diversity.

its inventors. The authors argue that this provides a more conducive and efficient environment for innovation.

What emerges from the preceding discussion is that greater board diversity improves the firm's engagement with innovation and the efficiency of innovative processes. Although these studies do not focus on IPO firms, we hypothesize a similar relationship for such firms.

H1a: Greater board diversity increases innovative efficiency in IPO firms.

To develop a competing hypothesis, we draw on Forbes and Milliken's (1999) diversity theory according to which an increase in diverse views results in greater board cohesiveness. Still, such diverse perspectives may inhibit the board's effectiveness in decision-making via cognitive conflicts. Forbes and Milliken (1999, p. 494) define cognitive conflicts as "task-oriented differences in judgement among group members". They argue that, although cognitive conflicts contribute to the quality of strategic decisions, in uncertain environments such conflicts slow down decision-making. Torchia et al. (2015) provide empirical support for this argument as they find that board diversity results in higher levels of board creativity and cognitive conflicts, which in turn slow down decision-making.

Similarly, we argue that IPO firms with diverse boards may face difficulties reaching a consensus on critical decisions about investment in innovation due to a larger knowledge base, more external contacts, and greater access to information. The resulting potential resource overload of the board may then cause the firm to miss out on investing in viable, innovative projects. In support of this argument, Belkacemi et al. (2021) find evidence suggesting a negative relationship between board diversity and innovation performance.[5] They focus on the world's top 100 innovative firms in 2017 as per Forbes and study the impact of professional expertise diversity and educational diversity on innovative performance. They explain their findings by arguing that board members with different types of expertise are more likely to provide different viewpoints, ideas, and opinions, which increase the potential for conflicts during decision-making on innovation. Accordingly, we expect that IPO firms with greater board diversity experience more cognitive conflicts due to different perspectives, resulting in longer deliberations, consistent with the diversity theory. One such issue that the board may deliberate on is how the firm converts its R&D expenditure into patents, i.e., how it achieves innovative efficiency.

[5] They measure innovative performance by the difference between the firm's market capitalization and the present value of its cash flows.

Hence, differing perspectives may result in divergent opinions about whether the outcome of innovation projects is patent worthy, thereby creating conflicts in the boardroom. Such conflicts impede board effectiveness and slow down decision-making. As the US operates a “first inventor to file” system in granting patents under the America Invents Act of 2011, regardless of who came up with the idea, conflicts arising from greater board diversity may slow down patent filing, causing the firm to miss out on patenting opportunities. Accordingly, we hypothesize that greater board diversity decreases the efficiency of the innovative process, consistent with the diversity theory. This leads to the second, competing hypothesis:

H1b: Greater board diversity decreases innovative efficiency in IPO firms.

3. Data and Methodology

3.1. Sample Selection and Data Sources

The sample is drawn from the population of the IPOs completed on the NASDAQ, NYSE, and AMEX between January 1st, 1997, and December 31st, 2015. As we track each IPO for up to five years after going public, our period of study effectively ends on December 31st, 2020. In line with Boone et al. (2007) and Chahine et al. (2011), we exclude all American depository receipts (ADRs), real estate investment trusts (REITs), unit offerings, spin-offs, carve-outs, closed-end funds, financial firms with Standard Industrial Classification codes (SIC) codes 6000 to 6799, and so-called penny stocks, i.e., IPOs with an offer price below $5. For a firm to be included in the sample, it must be incorporated in the US at the offer date and be included in both the Center for Research in Security Prices (CRSP) and Compustat databases. These criteria yield an initial population of 2,641 IPO firms. From this population, we randomly select a final sample of 661 IPO firms, which amounts to 25% of the initial population. The use of a random sample is due to the time-intensive nature of hand collecting board data. The board data are hand collected from the offering prospectuses for the pre-IPO year and the IPO year, and proxy statements for the subsequent five years. Data on innovative input, i.e., data on R&D intensity, is collected from Compustat. The patent data is sourced from the Darden School of Business Patent Database created by Bena et al. (2017) and the updated KPSS patent database of Kogan et al. (2017). CRSP is the source for the financial data used in this paper.

Table 1 shows the distribution across time and industries of the random sample of 661 firms and the population of 2,641 IPOs. Panel A shows that the distribution across time of the sample is similar to that of the population. During the period of regulatory change caused by the SOX Act, i.e., 2001-2003, there is a decrease in the number of new listings as reflected in both the sample and the population. Similarly, there is a decrease in IPOs during the aftermath of the 2008 financial crisis for both the sample and the population of IPOs. Panel B shows the distribution across industries (based on the Fama-French 12 industry classification but excluding the finance industry) for the sample and the population. The business equipment industry is the largest industry in the sample and the second largest in the population: It makes up about a third of the sample and the population. The healthcare industry has the second largest number of IPOs, which amounts to 12% of the IPO population and it is represented in the final sample. The industry with the smallest number of IPOs, the utilities industry, accounts for about 1% of both the sample and the population. Hence, our sample of IPO firms represents the wider population of IPO firms.

[Insert Table 1 about here]

3.2 Models and Definition of Variables

We test the validity of hypotheses 1a and 1b on whether greater board diversity results in higher and lower levels, respectively, of innovative efficiency using fixed effects regressions. The dependent variable, innovative efficiency, is measured in the following two ways: First, based on patent count using Sinagl and Wang's (2021) sophisticated measure of how efficiently IPO firms turn R&D expenditure into patents, and second, based on patent citations. The first measure focuses on the quantity of innovative output, while the latter emphasizes quality. Following prior innovation literature (e.g., Guo and Zhou 2016), we set R&D expenditure to zero if it is not reported. Patent count is the total number of patents held by the IPO firm in the given year (Chen et al. 2018). Patent citations is the total number of citations received for the patents held by the IPO firm in the given year (Chen et al. 2018). Innovative efficiency is computed as the ratio of patents granted in the current period *t* scaled by the cumulative R&D expenditure starting in fiscal year *t*-6 and ending in year *t*-2, assuming a depreciation rate of 20%, following Hirshleifer et al. (2013). Only 67% of IPO firms in the sample were incorporated by fiscal year *t*-6. Hence, if a firm was not in existence or did not disclosure its R&D expenditure by fiscal year *t*-6, R&D expenditure is set to zero for that year (as well as any of the following years). In terms of innovative efficiency based on patent citations, this is the ratio of the number of citations received for patents held in the current period *t* scaled by the cumulative R&D expenditure starting in fiscal year *t*-6 and ending in year *t*-2, assuming a depreciation rate of 20%. Equation 1 shows the computation of innovative efficiency (Patent Count/5RDC or Patent Citations/5RDC).

$$\frac{Patent\ Count\ or\ Patent\ Citations}{5RDC_{i,t}} = \frac{Patents\ Granted_{i,t}\ \ or\ Number\ of\ Patent\ Citations_{i,t}}{R\&D\ _{i,t-2}+0.8*R\&D\ _{i,t-3}+0.6*R\&D\ _{i,t-4}+0.4*R\&D\ _{i,t-5}+0.2*R\&D\ _{i,t-6}}. \quad (1)$$

The rationale behind this approach is that prior R&D expenditure is the IPO firm's investment in innovative activity at the initial phase and should feed forward into the number of patents granted. Sinagl and Wang (2021) argue that it takes a firm five years to convert R&D expenditure into patents. Hall et al. (2001) show that patents are granted on average within two years of application by the US patent office, whereas Hirshleifer et al. (2013) argue that R&D expenditure over the preceding five years contributes to patent filings. Therefore, the cumulative R&D expenditure starts in year *t*-6 and ends in year *t*-2, which allows us to account for the time involved in the patent application process.

Equation 2 below relates to our baseline regression explaining innovative efficiency via board diversity, our key variable of interest. All independent variables are lagged by one year to ensure weak endogeneity.

$$Innovative\ Efficiency_{i,t} = \beta_0 + \beta_1 Board\ Diversity_{i,t-1} + \sum_{n=2}^{8} \beta_n Firm\ Characteristics_{i,t-1} + \sum_{n=9}^{12} \beta_n Board\ Characteristics_{i,t-1} + Firm\ Effects + Year\ Effects + \varepsilon_{i,t} \quad (2)$$

Index i designates the firm, while t refers to the fiscal year (year 0 being the year, which includes the IPO date). Importantly, despite our measure of innovative efficiency being based on the cumulative R&D expenditure starting in fiscal year *t*-6 and ending in year *t*-2, our IPO firms are typically younger and may therefore not be incorporated during the full six years before the IPO.[6] To this end, we test the robustness of our main result in section 5.2 using an alternative measure of innovative efficiency based on the cumulative R&D expenditure starting in fiscal year *t*-4 and ending in year *t*-2. Note that in our analysis, we include all our IPO firms and set the R&D expenditure for both years to zero if the firm was as yet not in existence or did not disclose its R&D expenditure.

As to the key independent variable, board diversity is measured in terms of gender, age, and professional expertise. Gender diversity is defined as the percentage of females in the boardroom (Sila et al. 2016). Age diversity is defined as the standard deviation of the board members' ages divided by the mean age of the board, using the coefficient of variation formula. High scores indicate greater age diversity (Ali et al. 2014). Professional expertise diversity is based on the Blau heterogeneity index using the proportions of each expertise category on the board. The index construction is based on Gray and Nowland (2017). The expertise categories include the academic, accountant, banker, consultant, dentist, doctor, engineer, executive, finance expert, IT expert, investment professional, lawyer, scientist, and politician expertise categories. The use of the Blau index for professional expertise diversity is appropriate as there are fourteen expertise categories, and this index accounts for the differences in each

[6] Ninety-one percent of IPO firms in the sample are in existence by year *t*-4, but only 67% of IPO firms were incorporated in year *t*-6.

category equally. The professional expertise diversity index is computed as $1 - \Sigma_{w=1}^{n} P_w^2$, where P_w is the proportion of board members in expertise category w. Higher scores for the index indicate higher professional expertise diversity. Additionally, this paper goes further by calculating each of the three measures of board diversity separately for the executive directors and non-executive directors.[7] This enables a more in-depth understanding of the impact of board diversity on innovative efficiency in IPO firms.

Furthermore, we control for various firm characteristics following Chen et al. (2018), i.e., firm age, firm size, ROA, risk, leverage, asset tangibility, and Tobin's Q. We also account for various board characteristics consistent with Balsmeier et al. (2017) and Chemmanur et al. (2014) by controlling for board size, board independence, board voting share ownership, venture capitalist (VC) board representation, and board connections. All variables are defined in Appendix A.

4. Results

4.1. Descriptive Statistics and Univariate Analysis

Descriptive Statistics

Table 2 reports descriptive statistics for all the firm-year observations between the year of the IPO, i.e., year 0, and year 5 post-IPO. All continuous variables are winsorised at the 1st and 99th percentiles to minimize the influence of outliers on our results. Panel A shows descriptive statistics for the measures of innovative efficiency. The sample firms are much larger with average total assets of $588 million, compared to Gounopoulos and Pham's (2018) mean of $475 million, while R&D expenditure is on average $20 million. Regarding patenting activity, IPO firms are on average granted 2 patents and such patents have on average 42 citations between the IPO year and year 5 post-IPO. A median of zero indicates that at least half of the sample have no patents. These descriptives are in contrast to those for more mature firms. For example, Chen et al.'s (2018) study on board diversity and innovation reports a mean of 5 patents granted and 10 citations for each of these patents. Nevertheless, IPO firms may have more novel patents from blue skies innovation that have a higher number of citations (Bernstein 2015), indicating greater innovative efficiency. In terms of innovative efficiency, Patent count/5RDC, has a mean value of 0.061, while Patent Citations/5RDC has a mean of 0.328. Hence, the IPO firms in our sample are granted fewer patents for each dollar of R&D expenditure compared to Chen et al.'s (2018) sample of mature listed firms, which are subsequently more impactful for innovation.

[7] The executive directors comprise the CEO and the other executives sitting on the board, while the non-executive directors consist of venture capitalist directors and other non-executives.

Panel B provides descriptives for the measures of board diversity. The mean gender diversity is 6%, while the median is 0%, suggesting that most firms across the sample period have no female directors on their boards. Compared to prior studies on mature firm, such as Chen et al. (2018) who report a mean female board representation of 9% and a median of 10%, gender diversity in our sample firms is much lower. This is consistent with expectations, as the pool of female directors is as yet limited and IPO firms may face more difficulties attracting female directors to their boards. The average age diversity reported is 0.167, which is close to the median of 0.166. Finally, the mean professional expertise diversity is 0.495, while the median is 0.512, indicating that roughly half of the board of IPO firms across the sample period have a diverse pool of professional experts. Considering that both age and professional expertise diversity range from 0 to 1, the summary statistics suggest that the IPO firms have a higher level of professional expertise diversity compared to age diversity in the boardroom. Across all measures of board diversity, we find that the non-executive directors on average have a higher level of board diversity compared to the executive directors.

Moving on to the control variables, Panel C reports the firm characteristics, while Panel D focuses on the board characteristics. In Panel C, the average firm age is 12 years, which is much less than the 19 years reported by Gounopoulos and Pham (2018) in their IPO study. Nevertheless, our IPO firms have not been recently incorporated and have had time to grow their assets since incorporation. A negative average return on assets (ROA) of -23% across the sample period suggests that the IPO firms still incur losses in the post-IPO period and this value is close to the -26% reported by Gounopoulos and Pham (2018). The average risk for all firm-year observations measured as the standard deviation of the return on assets is 32%, consistent with the negative ROA, while the average leverage is 19%. Asset tangibility across the sample period is on average 33%. The average Tobin's Q value of 3.105 for all firm-year observations suggests that firms in the sample are on average valued at three times their book value. Overall, the statistics for firm characteristics show that the IPO firms in the sample are younger compared to prior IPO studies, with a high level of risk, as expected for newly listed firms navigating the stock market for the first time.

Regarding the board characteristics, which are reported in Panel D, we find that there are on average 7 board members, 2 of which are executive directors and 5 non-executive directors across the sample period. The mean value for board independence is 73%, while the median is 77%. The board's voting share ownership across the sample period is on average 35% while the median value is 32%. This suggests that the directors have a significant influence on voted decisions. Unsurprisingly, 67% of firms across the sample period have venture capitalist directors on their boards. Beyond providing finance to the firm, venture capitalist directors create value-added through their screening activities, decision support, and connecting the firm with potential suppliers, customers, and employees (Iliev and Lowry 2020). An average of two board connections to other boards suggests that directors have sufficient experience from other board appointments that may influence decisions regarding innovation in the firm.

[Insert Table 2 about here]

While Table 2 reports the average levels of board diversity across the entire sample period, we also perform a trend analysis to examine whether and how these average levels change for the executive and non-executives over time. Figure 1 shows the trend analysis for executive and non-executive directors' board diversity across the sample period. In terms of gender diversity, the majority of female board members is non-executives, starting with an average of 4% in the pre-IPO year and growing to about 8% by year 5 post-IPO. In contrast, for the executive directors, there is a modest increase from 4% to 5% over the sample period. The trend analysis shows a decrease in age diversity for both the executives and non-executives during the sample period. However, there is a higher rate of decline from 0.047 in the pre-IPO year to 0.030 by year 5 post-IPO in age diversity for the executives, while non-executive directors' age diversity declines marginally from 0.151 to 0.149 over the same period. Finally, Figure 1 shows that professional expertise diversity for the executive directors declines from an average of 0.060 to 0.040, but it increases for the non-executive directors from 0.370 in the pre-IPO year to 0.512 in year 5 post-IPO. Hence, changes in the average levels of professional expertise diversity are largely due to the non-executive directors. To sum up, we observe changes in gender diversity for the non-executives, changes in age diversity for the executives, and changes in professional expertise diversity for the non-executives.

[Insert Figure 1 about here]

Univariate Analysis

Table 3 reports the univariate analysis of innovative efficiency. Firms with at least one female board member are compared to those without female board members, while firms with high (i.e., above median) age/professional expertise diversity are compared to those with low (i.e., below median) age/professional expertise diversity. For the sake of brevity, Panel A of Table 3 only reports the mean and median values and their significance for the t-tests for the differences in means and the Wilcoxon rank-sum tests for the differences in medians between the IPO firms in the high and low board diversity subsamples.

Across the sample period, firm-year observations with at least one female director have on average lower innovative efficiency (log (1+patent count/5RDC) = 0.061 and log (1+patent citations/5RDC) =0.326) compared to the firm-year observations without female directors (0.079 and

0.440). These differences are significant at the 5% level. The results are in contrast with Griffin et al.'s (2021) study on an international sample of mature listed firms as the latter reports a significantly positive difference in innovative efficiency between firm-year observations with female directors and those without female directors. Hence, our results suggest that IPO firms with female board representation are associated with fewer patents and citations for each dollar spent on research and development. Similarly, we find that IPO firms with higher levels of age diversity have lower innovative efficiency (0.064) compared to those with lower levels of age diversity (0.083). This difference is significant at the 5% level. For professional expertise diversity, the difference in the means of the measures of innovative efficiency between the high-level sub-sample and the low-level sub-sample is insignificant. All in all, the univariate analysis in Panel A of Table 3 suggests a negative relationship between board diversity and innovative efficiency. These patterns are consistent with H1b derived from the diversity theory (see Section 2), suggesting that greater board diversity increases cognitive conflicts in the boardroom and ultimately decreases the innovative efficiency of IPO firms. Thus, we find preliminary support for H1b that greater board diversity (of gender and age) decreases the innovative efficiency of IPO firms. In the main analysis, we examine diversity at a deeper level by distinguishing between executives and non-executives to unearth what drives this potentially negative impact.

Before proceeding with the multivariate analysis, we analyze the correlations between all our variables using the Pearson correlation coefficients to check for multicollinearity in Panel B of Table 3. The highest correlation coefficient is 0.685 and it is between the two measures for innovative efficiency. This is not surprising, as the two measures are computed similarly and the difference between the two is the focus on patents granted and patent citations. The second highest correlation coefficient of 0.349 is between leverage and asset tangibility. However, this is a moderate value, and the two variables are therefore jointly included in all our regressions.

4.2 The Impact of Board Diversity on Innovative Efficiency

Table 4 reports the fixed effects (FE) regression results for the impact of board diversity on innovative efficiency between the IPO year and year 5 post-IPO to test the validity of H1a and H1b.[8] Table 4 attempts to answer the question about whether and how board diversity influences the firm's effectiveness in generating patents and patent citations per dollar of R&D expenditure, referred to as

[8] All variables are winsorised at the 1% and 99% levels to mitigate the effect of outliers. The regressions control for year and industry fixed effects. The standard errors are heteroscedasticity consistent while the highest variance inflation factor (VIF) of 2.8 suggests that multicollinearity is not a problem in our model.

innovative efficiency. The dependent variable in columns 1 and 2, i.e., Log (1+Patent count/5RDC), is measured as the logarithm of one plus the ratio of patents granted in the current period *t* scaled by the cumulative R&D expenditure starting in the fiscal year *t*-6 and ending in the fiscal year *t*-2, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). In columns 3 and 4, Log (1+Patent citations/5RDC) is measured as the logarithm of one plus the ratio of the number of citations received for patents held in the current period *t* scaled by the prior cumulative R&D expenditure starting in the fiscal year *t*-6 and ending in the fiscal year *t*-2, again assuming a depreciation rate of 20%. Regarding the independent variables, columns 1 and 3 use the main measures of board diversity, i.e., gender, age, and professional expertise, while columns 2 and 4 use the decomposed measures of board diversity for the executives and non-executives.

Table 4 indicates that there is a negative relationship between executive directors' age diversity and innovative efficiency. These results are both observed in column 2 using innovative efficiency measured by patent count and in column 4 using innovative efficiency measured by patent citations. The results are significant at the 5% level or better. For executive directors' age diversity, the negative coefficient implies that IPO firms with greater board age diversity for the executive directors are less efficient in turning R&D expenditure into patents and patent citations. Further, a unit increase in executive directors' age diversity results in a 0.268 (1.171) unit decrease in innovative efficiency based on patent count (patent citations). Regarding the main measures of board diversity in columns 1 and 3, i.e., gender, age, and professional expertise, we find no evidence of a relationship with innovative efficiency. The non-significant results for gender diversity are in contrast to those from prior literature for mature firms that reports a positive relationship between gender diversity and innovative efficiency (Griffin et al. 2021). Taken together, the results for the impact of board diversity (i.e., executive directors' age) on innovative efficiency reported in Table 4 are consistent with H1b derived from the diversity theory and the univariate analysis results. Hence, our results shed light for the first time on the importance of age diversity for executive directors in the boardroom of IPO firms.

The results for the control variables across all columns of Table 4 suggest that older and larger IPO firms have greater innovative efficiency while IPO firms with higher risk have lower innovative efficiency. The coefficients on these control variables are significant at the 10% level or better. This indicates that boards in IPO firms that are older and larger generate more patents and citations per dollar of R&D expenditure. In contrast, we find a negative effect of firm risk on innovative efficiency. In terms of the board characteristics, we find that greater board independence and board voting share ownership increase innovative efficiency as measured by patent count and patent citations. These results are significant at the 10% level or better. The implication is that more independent boards are better during innovative processes to ensure that strategies are being implemented as planned (Balsmeier et al. 2017), and patents are granted as an outcome of the process. Furthermore, boards with greater voting share ownership, i.e., greater power over voted decisions, have a higher level of innovative efficiency in terms of the patent citations. Besides these control variables, none of the other variables has a significant relationship with innovative efficiency.

[Insert Table 4 about here]

Overall, Table 4 suggest that greater age diversity for the executive directors inhibits the IPO firm's effectiveness in generating patents and patent citations per dollar of R&D expenditure. In contrast, the other board characteristics, i.e., board independence and board voting share ownership, improve innovative efficiency in IPO firms while the main measures of gender, age, and professional expertise diversity have no significant impact on the latter. Regarding the hypotheses, we find support for H1b as age diversity for executive directors decreases rather than increases innovative efficiency.

4.3 Endogeneity

We check whether the results from Table 4 hold after controlling for endogeneity concerns. On the one hand, it is possible that greater board diversity influences innovative efficiency. On the other hand, it could be the case that directors with a given gender, age or professional expertise are attracted to IPO firms that are more efficient in innovation. Hence, the negative effect of board diversity on innovative efficiency we have observed may not be a causal effect. To account for this potential reverse causality, we apply the entropy balancing (EB), coined by Hainmueller (2012). This technique improves on propensity score matching (PSM). Entropy balancing (EB) adopts a weighing process using distributional properties that achieve covariate balance between the treatment and the control groups such that, except for the treatment, both groups are virtually indistinguishable (Chahine et al. 2020). While the PSM algorithm assigns a value of one to the matched firms and discards other observations, EB computes continuous weights for all observations in the control sample without discarding those with low similarity scores. Hence, the main benefit from using EB over PSM is that it preserves the entire sample, thereby improving the power of the tests. Furthermore, EB is more efficient and mitigates the researcher's discretion, as it is not sensitive to PSM parameters, such as matching type, caliper difference, or the choice of replacement. For these reasons, the identification strategy used in this paper is based on the EB rather than PSM matched samples. Note that, as a robustness, we also used PSM (the results are not tabulated) and we are able to confirm our key results.

The treated group in entropy balancing for gender diversity comprises firms with female directors, while the control group consists of firms without female directors. Regarding age and professional expertise diversity, we take a different approach by creating a high, i.e., treated, and a low, i.e., control, group based on median values, as these variables range between zero and one. Covariate balance between the treated and control firms is achieved by weighing the distribution properties of both groups using the following firm observable characteristics: firm age, firm size, ROA, risk, leverage, asset tangibility, and Tobin's Q. This approach allows us to achieve covariate balance of firm observables between firms with diversity in the boardroom and those without. Subsequently, we expect that there is no observable difference, except for the level of board diversity. We test the differences between the post-weighing means of covariates to ensure that proper entropy balancing has been achieved. Table 5 confirms that there are no statistically significant differences between the means of the treated and control groups post-EB, confirming that entropy balancing has been achieved.

[Insert Table 5 about here]

Table 6 reports the fixed effects regression results based on EB testing the robustness of the main results in Table 4 for the impact of board diversity on innovative efficiency. The dependent variable in columns 1 to 6, i.e., innovative efficiency, is measured as the ratio of patents granted in the current period *t* scaled by the cumulative R&D expenditure over the fiscal years *t*-6 to *t*-2 (Patent count/5RDC), assuming a depreciation rate of 20% as per Hirshleifer et al. (2013). In columns 7 to 12, innovative efficiency is measured as the ratio of the number of citations received for patents held in the current period *t* scaled by the prior cumulative R&D expenditure covering the fiscal years *t*-6 to *t*-2 (Patent citations/5RDC), also assuming a depreciation rate of 20%.

Consistent with the results from Table 4, we find evidence of a negative relationship between board age diversity for the executive directors and innovative efficiency in columns 5 and 11. In particular, the coefficient on executive director age diversity indicates that a unit increase results in a 0.296 (1.265) decrease in Patent count/5RDC (Patent citations/5RDC). The coefficient is significant at the 5% level or better. Hence, IPO firms with greater age diversity for the executive directors are less efficient in transforming R&D expenditure into patents and patent citations. These findings provide further support for H1b. For all the other columns of Table 6, there is no evidence of a relationship between the main measures of board diversity, i.e., gender, age, and professional expertise diversity, and the decomposed diversity measures on the one side and innovative efficiency on the other side. This is consistent with the results from Table 4. For the sake of brevity, we do not report the results for the control variables in Table 6. However, the results are similar to those in Table 4.

[Insert Table 6 about here]

Overall, the FE results based on EB are largely consistent with the main results. Hence, it is important to consider executive directors' age diversity in IPO firms, as this is detrimental to the efficiency of the innovation process. In summary, the findings from this analysis are consistent with the main results in Tables 4 and 6 suggesting that greater age diversity for the executive directors is detrimental to innovative efficiency.

Despite the focus of this section on EB, we explored other identification strategies i.e., PSM as aforementioned, instrumental variable (IV) estimation, and the generalized method of moments (GMM). Again, the results using the PSM sample in Table 6 are similar to the results using EB. As mentioned earlier, using PSM results in a loss of observations that reduces the power of the tests. In terms of the IV estimation, we used two stage least square regressions (2SLS). This identification strategy addresses potential reverse causality issues by extracting the exogenous components of board diversity to explain the innovative efficiency of IPO firms. Although we identified instruments for gender diversity (i.e., industry gender diversity)[9] and age diversity (local age diversity),[10] the task to locate another appropriate instrument for professional expertise diversity proved ineffectual.[11] Thus, we do not rely on the IV estimation as our main identification strategy in this paper. Finally, we explored the GMM estimation technique, which uses lags of the dependent variable (innovative efficiency) and the independent variables as internal instruments to mitigate simultaneous and dynamic endogeneity. Still, this identification strategy is inappropriate for two reasons. First, the dependent variable, i.e., innovative efficiency, is the ratio of the patent count or the patent citations to the cumulated R&D expenditure starting from year *t*-6 and ending in year *t*-2. Hence, the dependent variable inherently accounts for prior periods. Second, board diversity is largely persistent with significant jumps in years 2 and 5 post-IPO. This implies that dynamic endogeneity may not necessarily be an issue in the sample. For these reasons, we focus on EB as our main identification strategy.

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[9] Industry gender diversity is computed as the average gender diversity for each industry per year, excluding the IPO sample firms within that industry. The rationale for this instrument is that IPO firms in the same industry are more likely to conform to the board gender diversity norms in their industry to ensure comparability with mature firms in the industry.

[10] Local age diversity is the average board age diversity for each state, excluding firms in the sample, headquartered in that state. We argue that the average age diversity for each state where the IPO firm is headquartered is more likely to influence age diversity on the boards of the IPO firms as board age likely reflects the state demographics, which influence the supply of directors.

[11] We explore several instruments for professional expertise, which fail all the Craig Donald Wald weak instrument test. These include, Local Director Supply, Regional Location dummies (West, Northeast, Midwest, South), Industry Director Supply, Industry Professional Expertise, and Industry Board Independence.

5. Robustness Analysis

5.1 The Role of Corporate Governance Quality

This analysis investigates whether the main findings in Table 4 vary across IPO firms depending on the quality of their corporate governance. The focus here is on corporate governance characteristics drawn from prior literature, arguing that board independence, board connections, and VC board representation improve innovation (Lu and Wang 2018, Chang and Wu 2021, Chemmanur et al. 2014). Accordingly, we expect that the negative impact of board diversity on innovative efficiency is more apparent in firms with weaker governance characteristics, i.e., poorly governed, poorly connected IPO firms, and IPO firms without VC board representation. We create indicator variables that are interacted with our main variables of interest (i.e., the measures of board diversity distinguishing between executive and non-executive directors) to examine the impact of IPO firms' governance quality on the results. The indicator variables for board independence and board connections are based on their median values. IPO firms with values above the median are considered well governed and better connected with a value of one, while those below the median are poorly governed and poorly connected with a value of zero, respectively. In terms of VC board representation, all firms with venture capitalist directors on the board take a value of one, and zero otherwise.

For the sake of brevity, Table 7 reports the results for the impact on innovative efficiency of the measures of board diversity distinguishing between executive and non-executive directors. The first three columns in Table 7 focus on innovative efficiency measured by patent count, while the last three columns report the results for innovative efficiency measured by patent citations. Columns 1 and 4 report the results for the interaction of the measures of board diversity and the indicator variable for board independence. In columns 2 and 5, we interact the measures of board diversity with the indicator for board connections, while columns 3 and 6 interact the former with VC board representation, respectively. Tables 8 and 9 are the equivalents of Tables 7 but are based on EB.

In line with our main results, Table 7 consistently shows that greater board age diversity for the executive directors negatively impacts the innovative efficiency of IPO firms. In detail, the coefficients suggest that the negative effect of executive directors' age diversity on innovative efficiency is larger when innovative efficiency is measured by patent citations rather than patent count. However, the non-significant results for all interaction terms in columns 1 to 6 indicate that our results remain unaffected by the quality of corporate governance of the IPO firms. Finally, across all columns of Table 7, we do not find any evidence of a relationship between the measures of board diversity in terms of gender or professional expertise for the executives and non-executives, and innovative efficiency, in line with the main results. The implication of these findings is that fewer patents and citations are generated for each dollar of R&D expenditure when executive directors' age diversity increases, regardless of the quality of corporate governance. Overall, the results in Table 7 are consistent with Field et al. (2013) suggesting that, for IPO firms, the monitoring role of the board is not as important as the advisory role.

[Insert Table 7 about here]

Table 8 reports the FE results using EB for moderating the effect of corporate governance quality on the relationship between the measures of board diversity for the executives and non-executives and innovative efficiency as measured by patent count. In columns 2, 5, and 8, we find similar evidence supporting the negative relationship between executive directors' age diversity and innovative efficiency as per the main results. Further, the interaction terms for board independence, board connections, and VC board representation are all non-significant similar to Table 7. Although our main results are robust, there is no evidence suggesting that the quality of corporate governance influences the negative impact of executive directors' age diversity on innovative efficiency. Additionally, the measures of board diversity in gender and professional expertise for the executives and non-executives have no influence on innovative efficiency as measured by patent count, congruous with the main results.

[Insert Table 8 about here]

Next, we investigate whether the FE results in Tables 7 are robust to EB in Table 9. Table 9 reports the results for innovative efficiency measured by patent citations. It is evident that the results from Table 7 remain robust when using EB in Table 9. Similarly, we find that greater executive directors' age diversity decreases innovative efficiency (Log (1+Patent citations/5RDC)), but this effect does not extend to the interaction terms. The interactions of the measures of board diversity for the executives and non-executives on the one side and board independence, board connections, and VC board representation on the other side remain non-significant. This is consistent with the results from Table 7 and this confirms our finding that the negative impact of executive directors' age diversity on innovative efficiency is not influenced by the quality of governance of the IPO firms. Finally, we also observe that there is no significant relationship between the interactions for the measures of board gender and age diversity for the executives and non-executives on the one side and XYZ on the other side and innovative efficiency in Table 9, similar to the results in Table 7.

[Insert Table 9 about here]

Put together, the results in this section show that the detrimental effect of executive directors' age diversity on innovative efficiency is not influenced by the governance quality of the IPO firms. Hence, this section provides support for prior literature suggesting that the monitoring role of the board is not as important in IPO firms, and we find that this is the case in relation to the efficiency of the innovation process.

5.2 Alternative Measure of Innovative Efficiency

In this section, we test the robustness of the main results using an innovative efficiency measure based on the cumulative R&D expenditure starting in fiscal year *t*-4 and ending in year *t*-2. By year *t*-4, 91% of IPO firms in the sample are in existence and if a firm was not in existence or did not disclosure its R&D expenditure in a given year R&D expenditure is set to zero. The rationale for this measure using the three-year cumulative R&D expenditure is that IPOs are typically younger and may not have been founded by year *t*-6.[12] Table 10 reports the results for the impact of board diversity on this alternative measure of innovative efficiency. For brevity, we focus on the decomposed measures of board diversity. We report the results using FE regressions and FE regressions using EB. The first four columns of Table 10 relate to innovative efficiency measured by patent count, while the last 4 report the results for the dependent variable measured by patent citations. Similar to the main results from Tables 4 and 6, we find that greater executive directors' age diversity is detrimental to innovative efficiency. This result is significant at the 5% level or better. More specifically, a one-unit increase in executive directors' age diversity decreases patents generated by 0.268 to 0.297 units and patent citations by 1.269 to 1.171 units for each dollar of R&D expenditure. Hence, IPO firms with greater executive directors' age diversity in the boardroom are less efficient during the innovative process. In summary, the results reported in Table 10 using an alternative definition of innovative efficiency are consistent with main results.

[Insert Table 10 about here]

Overall, we find that the main results are robust when we account for the quality of corporate governance, despite these corporate governance factors having no moderating effect. Finally, the main results are also robust to an alternative measure of innovative efficiency based on a shorter period for R&D expenditure.

6. Conclusion

We attempt to fill the gap in the literature by analyzing how board diversity (i.e., gender, age, and professional expertise) influences the IPO firm's effectiveness in generating patents and patent citations for each dollar of R&D expenditure, referred to as innovative efficiency. The main findings in this paper suggest that executive directors' age diversity has a negative impact on innovative efficiency. In terms

[12] Hence, innovative efficiency is computed as follows:

$$Patent\ Count\ or\ Patent\ Citations/3RDC_{\ i,t} = \frac{Patents\ Granted_{i,t}\ \ or\ Number\ of\ Patent\ Citations_{i,t}}{R\&D_{\ i,t-2}+0.8*R\&D_{\ i,t-3}+0.6*R\&D_{\ i,t-4}}$$

of gender and professional expertise diversity, we find no evidence of a relationship between the various measures of board diversity and innovative efficiency. All the above results are robust to econometric specifications and alternative measures of innovative efficiency.

In the robustness analysis, we attempt to explain the reasons behind the main findings by interacting the measures of board diversity with corporate governance characteristics, i.e., board independence, board connections, and VC board representation. Although we find that the negative effect of executive directors' age diversity holds, these this negative relation is not moderated by the quality of governance of the IPO firms.

The results highlight the importance of executive directors' age diversity during the innovative process for IPO firms, which has implications for potential issuers and regulators. This paper provides vital information to potential issuers on board characteristics to consider in structuring their boards. To ensure the efficiency of the innovative process, IPO firms should consider executive directors' age diversity in the boardroom. Furthermore, focusing on other board characteristics, voting share ownership has a positive effect for the quality of patents generated during the innovative process.

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Main Figures and Tables

Figure 1. Average Executive and Non-Executive Directors Board Diversity across the sample period.

Figure 1 demonstrates the time trend across the sample period for diversity within the executive and non-executive director groups in terms of gender, age and professional expertise. Executive directors are board members that are employees of the firm such as the CEO or other executives, while all other directors are non-executives such as venture capitalist represented on the board. All the variables are defined in Appendix A.

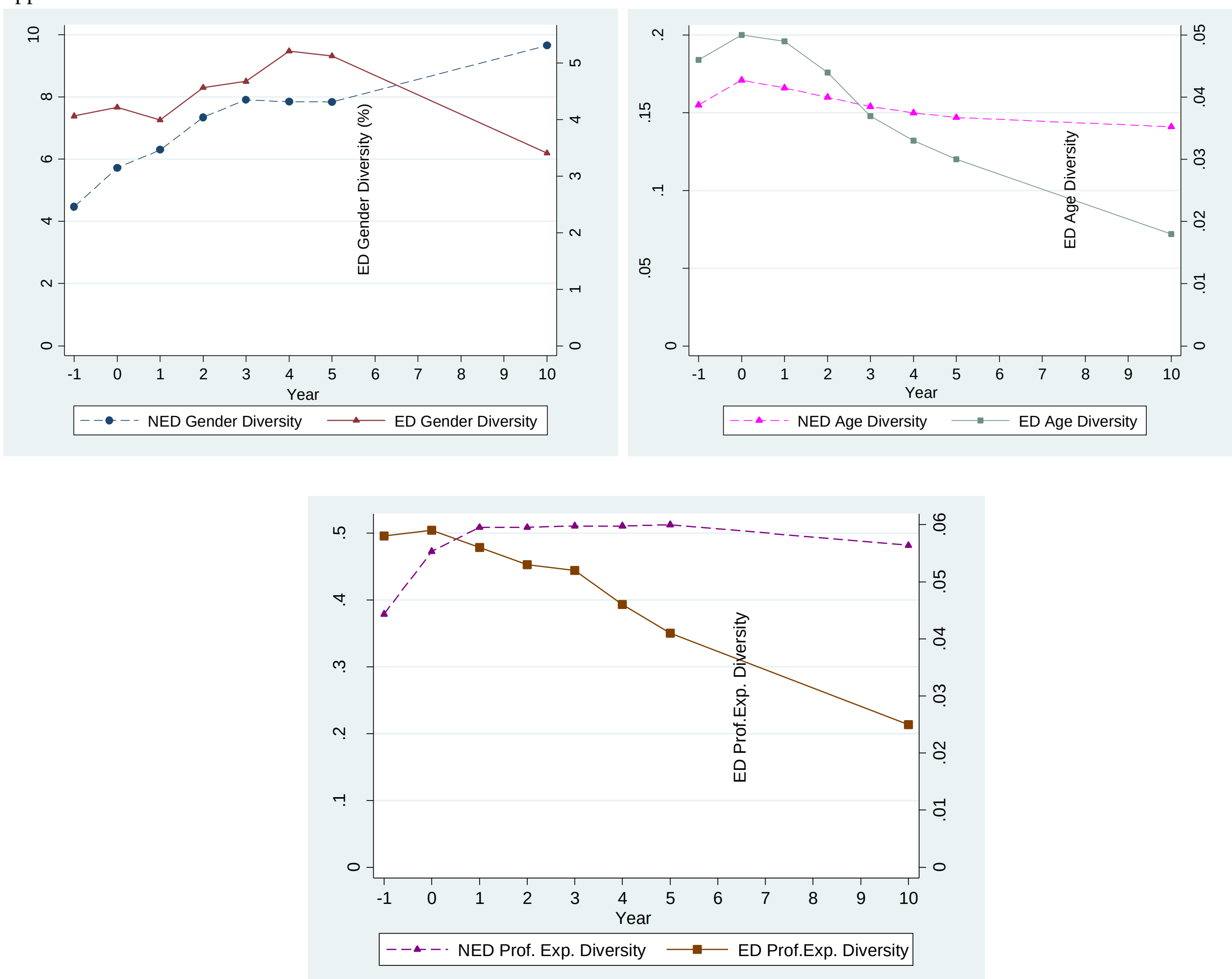

Table 1. The Sample Distribution by Year and by Industry

This table shows the distribution across time and industries for the random sample of 661 IPOs as compared to the population of 2641 IPO firms conducted in the US between 1997 and 2015. Panel A reports the distribution of IPOs by year for the sample and the population. Panel B reports the distribution across industries for the sample and the entire population using the Fama and French 12 industry classification. As stated in Section 3.1, IPOs in the financial industry are excluded from the sample.

Panel A: IPO Distribution by Year for the Sample and Population

Year	Sample N=661	Percentage	Population N=2461	Percentage
1997	95	14.37	400	15.15
1998	62	9.38	232	8.78
1999	87	13.16	408	15.45
2000	80	12.10	312	11.81
2001	14	2.12	60	2.27
2002	10	1.51	50	1.89
2003	7	1.06	50	1.89
2004	28	4.24	134	5.07
2005	21	3.18	124	4.7
2006	27	4.08	119	4.51
2007	36	5.45	119	4.51
2008	5	0.76	17	0.64
2009	13	1.97	35	1.33
2010	18	2.72	64	2.42
2011	25	3.78	63	2.39
2012	20	3.03	81	3.07
2013	33	4.99	119	4.51
2014	52	7.87	155	5.87
2015	28	4.24	99	3.75
Total	661	100	2641	100

Panel B: Fama and French Industry Classification for Final Sample and Population at the IPO

Industry	Sample N=661	Percentage	Population N=2461	Percentage
Consumer non-durables	21	3.18	81	3.07
Consumer durables	10	1.51	28	1.06
Manufacturing	35	5.30	122	4.62
Oil, gas and coal extraction and products	16	2.42	79	2.99
Chemical and allied products	6	0.91	30	1.14
Business equipment	226	34.19	777	29.42
Telephone and television transmission	33	4.99	133	5.04
Utilities	4	0.61	20	0.76
Wholesale, retail, and some services	79	11.95	235	8.90
Healthcare, medical equipment and drugs	132	19.97	306	11.59
Other	99	14.98	830	31.43
Total	661	100	2641	100

Table 2. Summary Statistics

This table provides descriptive statistics for the 661 IPO sample firms from the IPO year (year 0) up to five years post-IPO (year 5). Total Assets is the value of total assets. R&D Expenditure is research and development expenditure. Patent Count is the number of patents held by the IPO firm in each year. Patent Citations is the total number of citations received for the patents held by the IPO firm in the given year. Patent Count/5RDC is the innovative efficiency measure based on the patents granted in year t scaled by the prior cumulative R&D expenditure starting in year t-2 up to year t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). Patent Citations/5RDC is the innovative efficiency measure based on the number of citations received for patents held in the current period (year t), scaled by the prior cumulative R&D expenditure starting in year t-2 up to year t-6, again assuming a depreciation rate of 20% following Hirshleifer et al. (2013). Gender Diversity is the percentage of females on the board. Age Diversity is measured as the coefficient of variation, i.e. the standard deviation of Board Age to the mean of Board Age. Professional Expertise Diversity is the Blau index, and it is computed as $1 - \Sigma_{i=1}^{n} P_i^2$ where Pi is the proportion of the board members in each of the i categories. Firm Age is the difference between the year of incorporation of the firm and the year of the IPO. Return on assets is earnings before interest, taxes, depreciation, and amortization divided by total assets. Risk is the prior three fiscal years rolling standard deviation of the return on assets. Leverage is the ratio of long-term debt to the total assets. Tobin's Q is the market value of equity plus the book value of total assets minus the book value of equity, all divided by the book value of total assets. Board Size is the number of directors on the board in each year. Board Independence is the percentage of independent directors on the board relative to board size. Board Voting Share Ownership is the total percentage of voting shares held by the board. VC Board Representation takes a value of one if a venture capitalist director is present on the board, and zero otherwise. Board Connections is the average number of prior and current board appointments of the board in the given year. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	N	Mean	Median	St. Dev	Min	Max
Panel A: Measures of Innovative Efficiency						
Total Assets ($b)	3193	0.588	0.143	1.293	0.002	8.586
R&D Expenditure ($b)	3198	0.020	0.004	0.053	0.000	1.049
Patent Count	3198	2.076	0.000	5.975	0.000	129.000
Patent Citations	3198	42.188	0.000	162.160	0.000	1168.000
Log (1+Patent Count /5RDC)	3198	0.061	0.000	0.197	0.000	3.026
Log (1+Patent Citations/5RDC)	3198	0.328	0.000	0.905	0.000	6.759
Panel B: Measures of Board Diversity						
Gender Diversity (%)	3198	6.336	0.000	10.027	0.000	80.000
ED Gender Diversity (%)	3198	4.353	0.000	17.626	0.000	100.000
NED Gender Diversity (%)	3198	6.411	0.000	10.906	0.000	80.000
Age Diversity	3198	0.167	0.166	0.060	0.000	0.534
ED Age Diversity	3198	0.043	0.000	0.081	0.000	0.437
NED Age Diversity	3198	0.160	0.163	0.070	0.000	0.459
Professional Expertise Diversity	3198	0.495	0.512	0.186	0.000	0.859
ED Professional Expertise Diversity	3198	0.053	0.000	0.153	0.000	0.750
NED Professional Expertise Diversity	3198	0.477	0.500	0.210	0.000	0.833
Panel C: Firm Characteristics						
Firm Age	3198	12.058	9.000	12.641	1.000	78.000
Return on Assets (%)	3170	-0.235	-0.041	0.546	-3.339	0.276
Risk	3179	0.318	0.078	0.702	0.002	4.163
Leverage	3170	0.189	0.045	0.262	0.000	1.158
Asset Tangibility	3168	0.328	0.209	0.323	0.000	1.540
Tobin's Q	3168	3.105	2.046	3.766	0.379	30.070
Panel D: Board Characteristics						
Board Size	3198	6.908	7.000	1.941	2.000	14.000
ED Board Representation	3198	1.531	1.000	0.802	0.000	10.000
NED Board Representation	3198	5.435	5.000	2.108	0.000	13.000
Board Independence (%)	3198	72.624	77.778	18.037	0.000	90.909
Board Voting Share Ownership (%)	3198	34.796	31.503	27.179	0.000	98.172
VC Board Representation	3198	0.673	1.000	0.469	0.000	1.000
Board Connections	3198	1.722	1.500	1.155	0.000	5.833

Table 3. Univariate Analysis and Correlation Matrix

This table reports the univariate analysis results for the impact of board diversity on innovative efficiency in Panel A, and the Pearson correlation matrix for all variables in Panel B. Panel A reports the t-test (Wilcoxon rank-sum test) for the difference in means (medians) between firm-year observations with at least one female director on the board and those without female directors, and between firm-year observations with high compared to low age and professional expertise diversity. The respective median values of the sample are used to categorize the firm-year observations into high and low sub-samples. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Univariate Analysis	Firms with at Least One Female Director N=998		Firms without Female Directors N=2044		Firms with High Age Diversity N=1521		Firms with Low Age Diversity N=1521		Firms with High Prof. Exp. Diversity N=1520		Firms with Low Prof. Exp. Diversity N=1522	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Log (1+Patent Count /5RDC)	0.061**	0.000	0.079	0.000	0.064**	0.000	0.083	0.000	0.079	0.000	0.067	0.000
Log (1+Patent Citations/5RDC)	0.326***	0.000	0.440	0.000	0.383	0.000	0.423	0.000	0.388	0.000	0.418	0.000

	Panel B: Correlation Matrix	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1	Log (1+Patent Count /5RDC)	1.000															
2	Log (1+Patent Citations/5RDC)	0.694*	1.000														
3	Gender Diversity	-0.024	-0.032	1.000													
4	Age Diversity	-0.042*	-0.016	-0.083*	1.000												
5	Prof. Exp. Diversity	0.047*	0.031	0.036	0.110*	1.000											
6	Firm Age	-0.011	-0.051*	0.026	-0.057*	-0.004	1.000										
7	Firm Size	-0.070*	-0.046*	0.083*	-0.084*	0.064*	0.251*	1.000									
8	ROA	-0.023	-0.055*	0.018	-0.058*	-0.077*	0.177*	0.454*	1.000								
9	Risk	-0.001	0.003	-0.062*	0.083*	-0.004	-0.170*	-0.347*	-0.472*	1.000							
10	Leverage	-0.108*	-0.124*	0.002	0.006	0.045*	0.159*	0.362*	0.044*	-0.041*	1.000						
11	Asset Tangibility	-0.076*	-0.102*	-0.066*	-0.008	-0.047*	0.096*	0.091*	-0.026	-0.038	0.292*	1.000					
12	Tobin's Q	0.062*	0.101*	0.058*	0.034	0.065*	-0.120*	-0.153*	-0.299*	0.174*	-0.085*	-0.127*	1.000				
13	Board Size	0.006	-0.008	0.139*	0.026	0.229*	0.132*	0.426*	0.093*	-0.146*	0.156*	0.030	0.009	1.000			
14	Board Independence	0.063*	0.069*	0.079*	0.004	0.274*	0.056*	0.287*	0.051*	-0.110*	0.099*	0.025	0.032	0.447*	1.000		
15	Board Voting Share Ownership	-0.044*	-0.083*	-0.025	0.183*	0.042*	-0.076*	-0.185*	0.009	0.040	0.051*	-0.047*	0.018	-0.127*	-0.176*	1.000	
16	VC Board Rep.	0.036	0.073*	0.041	0.087*	0.352*	-0.093*	0.116*	-0.011	-0.032	0.024	-0.091*	0.091*	0.197*	0.273*	0.169*	1.000
17	Board Connections	-0.025	-0.040	0.103*	-0.046*	0.148*	0.007	0.227*	-0.022	-0.012	0.150*	-0.087*	0.019	0.225*	0.265*	0.015	0.220*

Table 4. Testing the Impact of Board Diversity on Innovative Efficiency Using Fixed Effects

This table reports the OLS regressions for the effect of board diversity on innovative efficiency using the sample of firm-year observations from the IPO year to year 5 post-IPO. In columns 1 and 2, innovative efficiency in is measured as the ratio of patents granted in the current period t scaled by the prior cumulative R&D expenditure starting in the fiscal year t-2 to t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). The lag for cumulative R&D expenditure accounts for the two-year patent application-grant period. In columns 3 and 4, innovative efficiency is measured as the ratio of the number of citations received for patents held in the current period t scaled by the cumulative R&D expenditure starting in the fiscal year t-2 to t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). All the variables are defined in Appendix A. The t values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by IPO firms. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	Log (1+Patent Count/5RDC $_t$)		Log (1+Patent Citations/5RDC $_t$)	
	(1)	(2)	(3)	(4)
Gender Diversity $_{t-1}$	0.001		0.001	
	(0.96)		(0.43)	
Age Diversity $_{t-1}$	-0.169		-0.275	
	(-1.24)		(-0.64)	
Prof. Exp. Diversity $_{t-1}$	0.034		0.035	
	(0.84)		(0.22)	
ED Gender Diversity $_{t-1}$		0.001		0.000
		(0.84)		(0.06)
NED Gender Diversity $_{t-1}$		0.001		0.001
		(1.11)		(0.28)
ED Age Diversity $_{t-1}$		-0.268**		-1.171***
		(-2.52)		(-2.81)
NED Age Diversity $_{t-1}$		-0.031		-0.187
		(-0.27)		(-0.55)
ED Prof. Exp. Diversity $_{t-1}$		0.027		-0.087
		(0.57)		(-0.41)
NED Prof. Exp. Diversity $_{t-1}$		-0.002		-0.010
		(-0.06)		(-0.07)
Firm Age $_{t-1}$	-0.001	-0.002	0.020*	0.019*
	(-0.54)	(-0.68)	(1.77)	(1.83)
Firm Size $_{t-1}$	0.014	0.014	0.131***	0.132***
	(1.63)	(1.64)	(3.29)	(3.31)
Return on Assets $_{t-1}$	-0.008	-0.008	-0.072	-0.072
	(-0.71)	(-0.73)	(-1.11)	(-1.13)
Risk $_{t-1}$	-0.011	-0.011	-0.065*	-0.068*
	(-1.15)	(-1.19)	(-1.71)	(-1.87)
Leverage $_{t-1}$	-0.023	-0.026	-0.158	-0.181*
	(-1.22)	(-1.39)	(-1.51)	(-1.74)
Asset Tangibility $_{t-1}$	0.039	0.044*	0.043	0.065
	(1.57)	(1.76)	(0.37)	(0.56)
Tobin's Q $_{t-1}$	-0.002*	-0.002*	0.008	0.008
	(-1.82)	(-1.85)	(1.04)	(1.01)
Board Size	-0.004	-0.001	0.003	0.017
	(-1.19)	(-0.34)	(0.25)	(1.20)
Board Independence $_{t-1}$	0.001*	0.000	0.000	-0.001
	(1.91)	(1.21)	(0.31)	(-0.36)
Board Voting Share Ownership $_{t-1}$	0.000	0.000	0.002***	0.002***
	(1.39)	(1.21)	(2.77)	(2.69)
VC Board Representation $_{t-1}$	0.012	0.015	-0.011	-0.007
	(0.81)	(0.95)	(-0.15)	(-0.09)
Board Connections $_{t-1}$	0.001	0.000	-0.003	-0.003
	(0.10)	(0.05)	(-0.11)	(-0.08)
Constant	0.098*	0.099**	-0.268	-0.204
	(1.92)	(2.13)	(-1.19)	(-0.93)
Firm and Year Effects	Yes	Yes	Yes	Yes
No of observations	3042	3042	3042	3042
Adjusted R^2	0.029	0.030	0.033	0.036
F-value	2.341***	2.311***	2.229***	2.316***

Table 5. Entropy Balancing: Diagnostic Test on the Differences in Covariates Post-Match

This table reports the entropy balancing results that ensure better covariate balance between the treated firms and control groups by weighing observations such that the post-weighing mean for treated and control samples are equal along the matching dimensions. Panel A reports the diagnostic tests relating to gender diversity, Panel B reports the results for age diversity while Panel C provides the results relating to professional expertise diversity. We report the standardised mean differences for treated and re-weighted control samples, as well as the variance ratio comparing both samples to show that entropy balancing is achieved. After re-weighing the observations, the mean difference is on average zero while the variance ratio is on average one in all Panels.

	Treated			Control				
	Mean	Variance	Skewness	Mean	Variance	Skewness	Std Mean Diff	Variance Ratio
Panel A: Gender Diversity		N=210			N=451			
Firm Age	12.498	126.705	2.819	12.498	166.393	3.013	0.000	0.761
Firm Size	5.227	2.747	0.131	5.227	2.747	0.131	0.000	1.000
Return on Assets	-0.241	0.305	-3.394	-0.241	0.306	-3.394	0.000	0.997
Risk	0.284	0.347	3.910	0.284	0.348	3.910	0.000	0.997
Leverage	0.187	0.072	1.638	0.187	0.072	1.638	0.000	1.000
Asset Tangibility	0.297	0.094	1.867	0.297	0.094	1.867	0.000	1.000
Tobin's Q	3.216	11.044	4.013	3.216	11.046	4.013	0.000	1.000
Panel B: Age Diversity		N=328			N=333			
Firm Age	12.820	182.290	2.725	12.819	155.136	2.979	0.000	1.175
Firm Size	5.170	2.965	0.028	5.169	2.964	0.028	0.000	1.000
Return on Assets	-0.230	0.320	-3.449	-0.231	0.320	-3.448	0.000	1.000
Risk	0.332	0.536	3.686	0.331	0.536	3.688	0.000	1.000
Leverage	0.202	0.076	1.488	0.202	0.076	1.489	0.000	1.000
Asset Tangibility	0.365	0.126	1.398	0.365	0.126	1.398	0.000	1.000
Tobin's Q	2.956	11.320	3.987	2.956	11.321	3.989	0.000	1.000
Panel C: Prof. Exp. Diversity		N=327			N=334			
Firm Age	12.917	162.869	3.071	12.917	182.664	2.738	0.000	0.892
Firm Size	5.227	2.656	0.085	5.227	2.656	0.085	0.000	1.000
Return on Assets	-0.252	0.295	-3.345	-0.252	0.295	-3.345	0.000	1.000
Risk	0.279	0.397	4.478	0.279	0.397	4.478	0.000	1.000
Leverage	0.194	0.069	1.619	0.194	0.069	1.619	0.000	1.000
Asset Tangibility	0.329	0.112	1.590	0.329	0.112	1.590	0.000	1.000
Tobin's Q	2.977	8.919	4.342	2.977	8.919	4.342	0.000	1.000

Table 6. Testing the Impact of Board Diversity on Innovative Efficiency Using Entropy Balancing

This table replicates Table 4 by re-estimating the fixed effects regressions using the entropy balancing approach to test the impact of board diversity on the innovative efficiency. The dependent variable, innovative efficiency, is measured in Panel A as the ratio of patents granted in year t scaled by the prior cumulative R&D expenditure starting in the fiscal year t-2 to t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). In Panel B, innovative efficiency is measured as the ratio of the number of citations received for patents held in year t scaled by the cumulative R&D expenditure starting in the fiscal year t-2 to t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). In columns 1 to 3 and 7 to 10, the main independent variables of interest are gender, age, and professional expertise diversity. These diversity measures are separated then into executive and non-executive in columns 4 to 6 and 10 to 12. All the variables are defined in Appendix A. The t values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by IPO firms. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	Log (1+Patent Count/5RDC $_{t}$)						Log (1+Patent Citations/5RDC) $_{t}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gender Diversity $_{t-1}$	0.001						0.003					
	(1.34)						(0.98)					
Age Diversity $_{t-1}$		-0.195						-0.402				
		(-1.22)						(-0.83)				
Prof. Exp. Diversity $_{t-1}$			0.007						-0.044			
			(0.19)						(-0.27)			
ED Gender Diversity $_{t-1}$				0.001						0.000		
				(1.24)						(0.40)		
NED Gender Diversity $_{t-1}$				0.001						0.002		
				(1.41)						(0.71)		
ED Age Diversity $_{t-1}$					-0.296**						-1.265***	
					(-2.29)						(-2.88)	
NED Age Diversity $_{t-1}$					-0.059						-0.315	
					(-0.45)						(-0.82)	
ED Prof. Exp. Diversity $_{t-1}$						-0.009						-0.210
						(-0.20)						(-0.97)
NED Prof. Exp. Diversity $_{t-1}$						-0.008						-0.068
						(-0.20)						(-0.49)
Constant	0.016	-0.023	-0.036	0.018	-0.026	-0.034	-0.597**	-0.694***	-0.598**	-0.591**	-0.670**	-0.594**
	(0.42)	(-0.44)	(-0.70)	(0.49)	(-0.53)	(-0.68)	(-2.37)	(-2.69)	(-2.23)	(-2.35)	(-2.58)	(-2.21)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	3042	3042	3042	3042	3042	3042	3042	3042	3042	3042	3042	3042
Adjusted R^2	0.401	0.379	0.401	0.401	0.381	0.401	0.543	0.551	0.574	0.543	0.553	0.574
F-value	1.437	1.696*	1.679*	1.395	1.964**	1.573*	2.738***	2.663***	2.511***	2.600***	3.193***	2.498***

Table 7. The Moderating Effect of Corporate Governance Quality on the Relationship Between Board Diversity and Innovative Efficiency

The fixed effects regression results reported in this table shed light on whether the main findings in Table 4 vary depending on IPO firms' quality of corporate governance. We create an indicator variable for board independence and board connections based on their median values. IPO firms with values above the median are considered well governed and better connected and the respective dummy variables take a value of one, while those below the median measures of diversity are poorly governed and poorly connected and the respective dummy variables take a value of zero. For VC board representation, firms with venture capitalist directors on the boards take a value of one and otherwise, zero. For brevity, we only report the three indicator variables interactions with the decomposed measures of board diversity to provide more context to the results. Innovative efficiency in columns 1 to 3 is measured as the logarithm of one plus the ratio of patents granted in the current period t scaled by the prior cumulative R&D expenditure starting in the fiscal year t-6 and ending in year t-2, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). In columns 4 to 6, innovative efficiency is measured as the logarithm of one plus the ratio of the number of citations received for patents held in the current period scaled by the cumulative R&D expenditure starting in the fiscal year t-6 and ending in year t-2, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). All the variables are defined in Appendix A. The t values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by IPO firms. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	Log (1+Patent Count/5RDC)$_t$			Log (1+Patent Citations/5RDC)$_t$		
Corporate Governance Dummy is measured as	Board Indepen-dence Dummy	Board Connec-tions Dummy	VC Board Represen-tation	Board Indepen-dence Dummy	Board Connec-tions Dummy	VC Board Represen-tation
	(1)	(2)	(3)	(4)	(5)	(6)
ED Gender Diversity $_{t-1}$	0.000	-0.001	-0.000	0.000	-0.001	-0.002
	(0.70)	(-0.72)	(-0.27)	(0.06)	(-0.54)	(-0.91)
NED Gender Diversity $_{t-1}$	0.001	0.000	0.002*	0.000	0.000	0.002
	(0.76)	(0.38)	(1.74)	(0.01)	(0.11)	(0.56)
ED Age Diversity $_{t-1}$	-0.316**	-0.261**	-0.375**	-1.235***	-1.292**	-1.091**
	(-2.48)	(-2.04)	(-2.01)	(-2.67)	(-2.41)	(-2.43)
NED Age Diversity $_{t-1}$	-0.025	0.005	-0.031	-0.205	-0.279	-0.074
	(-0.24)	(0.03)	(-0.16)	(-0.58)	(-0.59)	(-0.15)
ED Prof. Exp. Diversity $_{t-1}$	0.012	0.059	0.049	-0.060	0.121	-0.107
	(0.28)	(1.06)	(0.71)	(-0.27)	(0.45)	(-0.37)
NED Prof. Exp. Diversity $_{t-1}$	0.024	-0.015	-0.010	-0.034	0.035	-0.088
	(0.59)	(-0.32)	(-0.21)	(-0.26)	(0.20)	(-0.57)
Corp. Gov. Dummy $_{t-1}$	0.006	0.020	0.021	-0.052	0.072	-0.027
	(0.15)	(0.63)	(0.54)	(-0.35)	(0.65)	(-0.20)
ED Gender Diversity $_{t-1}$ * Corp.	0.000	0.002	0.001	-0.000	0.002	0.003
Gov. Dummy $_{t-1}$	(0.12)	(1.30)	(1.22)	(-0.10)	(0.83)	(1.38)
NED Gender Diversity $_{t-1}$ * Corp.	0.000	0.001	-0.002	0.001	0.001	-0.002
Gov. Dummy $_{t-1}$	(0.45)	(0.62)	(-1.58)	(0.42)	(0.15)	(-0.40)
ED Age Diversity $_{t-1}$ * Corp. Gov.	0.050	-0.018	0.170	0.394	0.349	-0.130
Dummy $_{t-1}$	(0.45)	(-0.12)	(0.95)	(0.85)	(0.56)	(-0.21)
NED Age Diversity $_{t-1}$ * Corp.	0.024	-0.068	-0.026	0.024	0.229	-0.192
Gov. Dummy $_{t-1}$	(0.13)	(-0.42)	(-0.14)	(0.04)	(0.39)	(-0.33)
ED Prof. Exp. Diversity $_{t-1}$ * Corp.	0.038	-0.084	-0.025	-0.061	-0.489*	0.042
Gov. Dummy $_{t-1}$	(0.44)	(-0.97)	(-0.30)	(-0.19)	(-1.69)	(0.13)
NED Prof. Exp. Diversity $_{t-1}$ *	-0.051	0.017	0.008	0.050	-0.111	0.121
Corp. Gov. Dummy $_{t-1}$	(-0.94)	(0.36)	(0.16)	(0.23)	(-0.57)	(0.62)
Constant	0.113**	0.091*	0.103**	-0.201	-0.230	-0.205
	(2.42)	(1.95)	(2.26)	(-0.91)	(-1.05)	(-0.93)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	3042	3042	3042	3042	3042	3042
Adjusted R^2	0.029	0.034	0.031	0.035	0.036	0.035
F-value	2.042***	2.052***	2.167***	2.053***	2.231***	2.076***

Table 8. The Moderating Effect of Corporate Governance Quality on the Relationship Between Board Diversity and Innovative Efficiency (Patent Count) Using Entropy Balancing

The fixed effects regression results reported in this table use the entropy balnacing approach to shed light on whether the main findings in Table 4 vary depending on the quality of corporate governance of IPO firms. Similar to the approach used in Table 7, we create an indicator variable for board independence and board connections based on their median values. IPO firms with values above the median are considered well governed and better connected and the respective dummy variables take a value of one, while those below the median measures of diversity are poorly governed and poorly connected and the respective dummy variables take a value of zero. For VC board representation, firms with venture capitalist directors on the boards take a value of one and otherwise, zero. The three indicator variables are interacted with the measures of board diversity to provide more context to the results. Innovative efficiency is measured as the ratio of patents granted in the current period t scaled by the prior cumulative R&D expenditure starting in the fiscal year t-2 to t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). All the variables are defined in Appendix A. The t values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by IPO firms. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Corporate Governance Dummy is measured as	Board Independence Dummy			Board Connections Dummy			VC Board Representation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ED Gender Diversity $_{t-1}$	0.001			-0.000			0.000		
	(1.55)			(-0.24)			(0.46)		
NED Gender Diversity $_{t-1}$	0.001			0.001			0.002*		
	(0.96)			(1.08)			(1.84)		
ED Age Diversity $_{t-1}$		-0.351**			-0.280*			-0.402**	
		(-2.38)			(-1.72)			(-2.07)	
NED Age Diversity $_{t-1}$		-0.044			-0.063			-0.073	
		(-0.36)			(-0.36)			(-0.34)	
ED Prof. Exp. Diversity $_{t-1}$			-0.034			0.025			-0.031
			(-0.91)			(0.52)			(-0.65)
NED Prof. Exp. Diversity $_{t-1}$			0.026			-0.022			0.016
			(0.61)			(-0.42)			(0.37)
Corp. Gov. Dummy $_{t-1}$	0.001	-0.020	0.025	0.024	0.020	0.009	0.019	0.004	0.028
	(0.04)	(-0.64)	(0.97)	(1.44)	(0.69)	(0.31)	(0.95)	(0.10)	(1.04)
ED Gender Diversity $_{t-1}$ *	-0.000			0.002			0.001		
Corp. Gov. Dummy $_{t-1}$	(-0.25)			(1.12)			(0.89)		
NED Gender Diversity $_{t-1}$ *	0.001			0.000			-0.002		
Corp. Gov. Dummy $_{t-1}$	(0.71)			(0.03)			(-1.36)		
ED Age Diversity $_{t-1}$ * Corp.		0.077			-0.035			0.198	
Gov. Dummy $_{t-1}$		(0.66)			(-0.22)			(1.21)	
NED Age Diversity $_{t-1}$ *		0.036			0.008			0.029	
Corp. Gov. Dummy $_{t-1}$		(0.19)			(0.05)			(0.14)	
ED Prof. Exp. Diversity $_{t-1}$ *			0.040			-0.075			0.036
Corp. Gov. Dummy $_{t-1}$			(0.45)			(-1.06)			(0.58)
NED Prof. Exp. Diversity $_{t-1}$ *			-0.053			0.035			-0.040
Corp. Gov. Dummy $_{t-1}$			(-0.99)			(0.67)			(-0.74)
Constant	0.037	-0.009	-0.012	0.016	-0.028	-0.031	0.017	-0.020	-0.034
	(0.98)	(-0.19)	(-0.23)	(0.41)	(-0.55)	(-0.57)	(0.45)	(-0.41)	(-0.67)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	3042	3042	3042	3042	3042	3042	3042	3042	3042
Adjusted R^2	0.401	0.381	0.400	0.405	0.381	0.401	0.402	0.381	0.401
F-value	1.221	1.681**	1.409	1.326	1.804**	1.599*	1.298	1.712**	1.404

Table 9. The Moderating Effect of Corporate Governance Quality on the Relationship Between Board Diversity and Innovative Efficiency (Patent Citation) Using Entropy Balancing

The fixed effects regression results reported in this table shed light on whether the main findings in Table 4 vary depending on the quality of corporate governance in IPO firms. We create an indicator variable for board independence and board connections based on their median values. IPO firms with values above the median are considered as well governed and better connected with a value of one, while those below the median are poorly governed and poorly connected with a value of zero, respectively. For VC board representation, firms with venture capitalist directors on the boards take a value of one and otherwise, zero. The three indicator variables are interacted with the measures of board diversity to provide more context to the results is measured as the ratio of the number of citations received for patents held in the current period scaled by the cumulative R&D expenditure starting in the fiscal year t-2 to t-6, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). All the variables are defined in Appendix A. The t values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by IPO firms. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

Corporate Governance Dummy is measured as	Board Independence Dummy			Board Connections Dummy			VC Board Representation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ED Gender Diversity $_{t-1}$	0.001			-0.000			-0.001		
	(0.75)			(-0.05)			(-0.43)		
NED Gender Diversity $_{t-1}$	0.001			0.002			0.002		
	(0.41)			(0.70)			(0.71)		
ED Age Diversity $_{t-1}$		-1.343***			-1.217**			-1.339***	
		(-2.81)			(-2.16)			(-2.61)	
NED Age Diversity $_{t-1}$		-0.371			-0.408			-0.334	
		(-0.93)			(-0.81)			(-0.60)	
ED Prof. Exp. Diversity $_{t-1}$			-0.195			-0.034			-0.261
			(-0.87)			(-0.13)			(-0.91)
NED Prof. Exp. Diversity $_{t-1}$			-0.065			-0.012			-0.077
			(-0.49)			(-0.07)			(-0.53)
Corp. Gov. Dummy $_{t-1}$	0.070	-0.043	0.043	0.070	0.019	0.136	-0.013	-0.016	-0.018
	(1.03)	(-0.39)	(0.35)	(1.07)	(0.23)	(1.25)	(-0.15)	(-0.15)	(-0.14)
ED Gender Diversity $_{t-1}$ *	-0.002			0.001			0.002		
Corp. Gov. Dummy $_{t-1}$	(-0.85)			(0.41)			(0.97)		
NED Gender Diversity $_{t-1}$ *	0.001			-0.001			-0.000		
Corp. Gov. Dummy $_{t-1}$	(0.31)			(-0.30)			(-0.11)		
ED Age Diversity $_{t-1}$ * Corp.		0.343			-0.095			0.139	
Gov. Dummy $_{t-1}$		(0.75)			(-0.16)			(0.24)	
NED Age Diversity $_{t-1}$ *		0.118			0.226			0.038	
Corp. Gov. Dummy $_{t-1}$		(0.19)			(0.40)			(0.06)	
ED Prof. Exp. Diversity $_{t-1}$ *			-0.043			-0.389			0.097
Corp. Gov. Dummy $_{t-1}$			(-0.13)			(-1.39)			(0.31)
NED Prof. Exp. Diversity $_{t-1}$ *			0.007			-0.129			0.015
Corp. Gov. Dummy $_{t-1}$			(0.03)			(-0.66)			(0.08)
Constant	-0.561**	-0.665***	-0.580**	-0.607**	-0.660**	-0.624**	-0.589**	-0.665**	-0.585**
	(-2.21)	(-2.63)	(-2.17)	(-2.42)	(-2.46)	(-2.27)	(-2.34)	(-2.54)	(-2.18)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	3042	3042	3042	3042	3042	3042	3042	3042	3042
Adjusted R^2	0.543	0.553	0.574	0.543	0.553	0.574	0.543	0.553	0.574
F-value	2.311***	2.808***	2.210***	2.583***	3.030***	2.607***	2.377***	2.811***	2.227***

Table 10. Robustness Analysis: Alternative Definition of Innovative Efficiency Based on 3-Year Cumulative R&D Expenditure

This table reports fixed effects results and fixed effects using entropy balancing testing the effect of board diversity on innovative efficiency between the IPO year and year 5 post-IPO. Columns 1 to 4 relate to innovative efficiency measured as the logarithm of one plus the ratio of patents granted in the current period scaled by the cumulative R&D expenditure starting in the fiscal year t-4 and ending in t-2, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). The ending period for the lag of cumulative R&D expenditure (t-2) accounts for the two-year period in which patent application are made and granted. In columns 5 to 8, innovative efficiency is measured as the logarithm of one plus the ratio of the number of citations received for patents held in the current period scaled by the cumulative R&D expenditure starting in the fiscal year t-4 and ending in year t-2, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). All independent and control variables are lagged one year relative to the dependent variable and defined in Appendix A. The standard errors are heteroscedasticity consistent. The figures in parentheses are the t-values. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	Log (1+Patent Count/3RDC) $_t$				Log (1+Patent Citations/3RDC) $_t$			
	FE		FE using EB		FE		FE using EB	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ED Gender Diversity $_{t-1}$	0.001	0.001			0.000	0.000		
	(0.85)	(1.26)			(0.01)	(0.33)		
NED Gender Diversity $_{t-1}$	0.001	0.001			0.001	0.002		
	(1.10)	(1.40)			(0.31)	(0.74)		
ED Age Diversity $_{t-1}$	-0.268**		-0.297**		-1.171***		-1.269***	
	(-2.49)		(-2.28)		(-2.77)		(-2.86)	
NED Age Diversity $_{t-1}$	-0.036		-0.063		-0.194		-0.321	
	(-0.32)		(-0.48)		(-0.57)		(-0.83)	
ED Prof. Exp. Diversity $_{t-1}$	0.022			-0.014	-0.102			-0.225
	(0.46)			(-0.33)	(-0.47)			(-1.02)
NED Prof. Exp. Diversity $_{t-1}$	0.002			-0.003	-0.001			-0.055
	(0.05)			(-0.08)	(-0.01)			(-0.40)
Constant	0.090*	0.026	-0.018	-0.026	-0.236	-0.571**	-0.651**	-0.574**
	(1.92)	(0.70)	(-0.37)	(-0.52)	(-1.07)	(-2.26)	(-2.49)	(-2.11)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	3042	3042	3042	3042	3042	3042	3042	3042
Adjusted R^2	0.026	0.412	0.393	0.412	0.033	0.548	0.559	0.580
F-value	2.135***	1.300**	1.877**	1.503***	2.183***	2.542***	3.126***	2.426***

Appendix A. Variable Definitions

This table presents the definitions of the variables used in the paper.

Variables	Definitions
Innovative Efficiency	
Patent Count/5Year RDC	The ratio of patent granted in the current period *t* scaled by the cumulative R&D expenditure starting in the fiscal year *t*-6 and ending in year *t*-2, assuming a depreciation rate of 20% following Hirshleifer et al. (2013). If a firm was not in existence or did not disclosure its R&D expenditure in a given year, R&D expenditure is set to zero. $Patent\ Count/5Year\ RDC_{\ i,t} = \frac{Patents\ Granted_{i,t}}{R\&D_{\ i,t-2}+0.8*R\&D_{\ i,t-3}+0.6*R\&D_{\ i,t-4}+0.4*R\&D_{\ i,t-5}+0.2*R\&D_{\ i,t-6}}$
Patent Citations/5Year RDC	The ratio of the number of citations received for patents held in the current period *t* scaled by the cumulative R&D expenditure starting in the fiscal year *t*-6 and ending in year *t*-2, assuming a depreciation rate of 20%. If a firm was not in existence or did not disclosure its R&D expenditure in a given year, R&D expenditure is set to zero. $Patent\ Citations/5Year\ RDC_{\ i,t} = \frac{Patent\ Citations_{i,t}}{R\&D_{\ i,t-2} + 0.8 * R\&D_{\ i,t-3} + 0.6 * R\&D_{\ i,t-4} + 0.4 * R\&D_{\ i,t-5} + 0.2 * R\&D_{\ i,t-6}}$
Board Diversity	
Gender Diversity	Percentage of females on the board of directors.
Age Diversity	The standard deviation of the board's age is divided by the mean age of the board. Using the coefficient of variation formula (SD of Board Age/ Mean of Board Age). Larger standard deviation (larger age differences between board members) and larger mean age (higher representation of young board members) would generate higher age diversity values. High scores indicate greater age diversity.
Professional Expertise Diversity	An expertise index based on the Blau index using the proportion of expertise groups on each board. Professional Expertise includes the following 14 categories: Academic, Accountant, Banker, Consultant, Dentist, Doctor, Engineer, Executive, Finance Expert, IT Expert, Investment Professional, Lawyer, Scientist, and Politician. It is computed as follows: $1 - \sum_{i=1}^{n} P_i^2$ Where Pi is the proportion of group members in each of the $i,$ categories. High scores indicate higher professional expertise diversity. For example, if all 7 board members are categorized as executives, then the index value will be 0, i.e., $1 - ((\frac{7}{7})^2)$ A board of 7 members with 2 IT experts, 1 executive, 2 investment professionals, 1 accountant and 1 finance expert will have an index value of 0.775, i.e., $1 - ((\frac{2}{7})^2 + (\frac{2}{7})^2 + (\frac{1}{7})^2 + (\frac{1}{7})^2 + (\frac{1}{7})^2)$. Thus, High scores indicate higher professional expertise diversity.
Control Variables	
Firm Age	The number of years since incorporation of the firm.
Firm Size	The natural log of total assets.
Return on Assets (ROA)	Earnings before interest, taxes, depreciation, and amortization divided by total assets.
Risk	The prior three fiscal years rolling standard deviation of the return on assets.
Leverage	The ratio of the book value of long-term debt to total assets.
Asset Tangibility	The net property, plant and equipment scaled by total assets
Tobin's Q	This is the market value of equity plus total assets minus the book value of equity, all divided by total assets. Market value of equity is calculated by multiplying the year-end closing price by the number of shares outstanding.
Board Size	The number of directors on the board.

Appendix A Continued	
Variables	Definitions
Board Independence	Percentage of independent directors on the board relative to board size. Director independence is measured in line with prior literature as a director who: is not a substantial shareholder of the firm up to 5%; had not been employed in any executive capacity by the company within the last 5 years; is not retained as a professional adviser by the company (either personally or through their firm); is not a significant supplier or customer of the company; has no significant contractual relationship with the company other than as a director.
Board Voting Share Ownership	The total percentage of voting shares owned by the board.
VC Board Representation	A dummy variable that takes a value of one if a Venture Capitalist Director is present on the board, and zero otherwise.
Board Connections	This is the average number of prior and current board appointments of the board in each year.