Gender Diversity Within the Executive Team and Innovation Performance: An Inter-Industry Comparison and Analysis

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**Abstract:**

* Seeks to evaluate whether there is a relationship between gender diversity within the executive teams of S&P 1500 companies and their innovation performance, as well as the direction and magnitude of this relationship
* Specifically, through using data from 1992 to 2006, this study finds no relationship between gender diversity and innovation performance in general except a strong positive correlation between gender diversity and innovation performance for Retail Trade
* It is also found that this relationship is very strong and positive for discrete industries and not significant for complex industries
* This paper incorporates relevant theories on the moderating effect of firm size, theories on knowledge capacity and its interaction with innovation, as well as the differences in patenting reasons

**1. Introduction**

Since the 1960s, discussion on the role of innovation has expanded rapidly (Garcia and Calantone, 2002). Innovation is commonly known as the introduction of something new and is recognized as an important engine of economic development and a driver of social progress, technological advancements, and sustainability (Garcia and Calantone, 2002). The idea of entrepreneurship was also introduced at the same time as the process of turning innovation into a business opportunity. On the other hand, rapid economic development in the last couple of decades was accompanied by a growing female labour participation rate. Indeed, there are 109,000 more women working than men in the U.S. as of December 2019 excluding farm workers and the self-employed (Kelly, 2021). Along this rapidly increasing female labour participation rate is the growing regulatory pressure on firms worldwide to address issues related to Diversity, Equity, and Inclusion including gender pay gaps and the under-representation of women in senior positions. Indeed, women made an increasing presence in top management teams in recent years for several Fortune 500 companies including General Motors, CVS Health, Citigroup, Oracle, and Best Buy. As a result, this paper seeks to investigate if and how gender diversity and innovation interact with the hope of contributing to the expanding literature on the intertwined relationship between innovation, entrepreneurship, and gender diversity.

* This study surprisingly finds that, given US does not have gender quotas and selection of the executive team would be based on performance, there is no relationship between gender diversity and innovation performance in general and for most of the industries except a strong positive correlation for firms in the Retail Trade industry
* It is also found that this relationship is very strong positive for discrete industries and not significant for complex industries
* This paper follows the below order: section 2 will provide with a brief literature review and detailed hypotheses, section 3 will present the dataset and summary statistics, section 4 will discuss the methodology, section 5 will provide the results and relevant discussion, and lastly section 6 will end this paper summarizing this paper’s contributions with limitations as well as suggestion for future research

**2. Literature Review and Hypotheses**

2.1 Gender diversity theories and studies

Diversity is “a characteristic of a group (of two or more people) which refers to demographic differences among group members in race, ethnicity, gender, social class, religion, nationality, sexual identity or other dimensions of social identity that are marked by a history of intergroup prejudice, stigma, discrimination, or oppression” (Ramarajan and Thomas, 2010). Specifically, there is an expanding literature on gender diversity and how it impacts firm value and a firm’s capabilities. Not only is the theoretical association between gender diversity and firm value commonly explored by scholars (Terjesen et al., 2009), many also focus on evaluating how gender diversity can impact different aspects of a firm empirically.

For instance, the link between gender diversity and firm performance has attracted substantial scholarly attention that provides different insights through different perspectives, lenses, and focuses. Carter et al. (2003) provide a holistic review of the theories and the positive impact of women on corporate boards (WOCB) at micro, meso, and macro levels: individual, board, firm, and industry/environment. Li and Chen (2018) and Simionescu et al. (2021), on the other hand, evaluate this positive relationship through a focus on Chinese firms and a focus on only the technology industry respectively. Scholars such as Ferrary and Déo (2022) also add to the discussion by establishing a similar relationship in the middle management and staff level of a firm instead of the board. However, although many studies provide evidence of a positive relationship (e.g., Carter et al., 2003; Ferrary and Déo, 2022; Li and Chen, 2018; Simionescu et al., 2021), others also provide evidence of no relationship (e.g., Chapple & Humphrey, 2014), a conditional relationship (e.g., Dwyer et al., 2013), or a negative relationship (e.g., Adams and Ferreira, 2009). Chapple and Humphrey (2014) do not find evidence of an association between board diversity and firm financial performance and weak evidence of a negative correlation between having multiple women on the board and performance. Dwyer et al. (2013), on the other hand, suggest how gender diversity's effects at the management level is conditional on the firm's strategic orientation, the organizational culture in which it resides, and the multivariate interaction among these variables. Last but not least, Adams and Ferreira (2009) indeed state an overall negative relationship between gender diversity and firm performance even when women are more active in joining committees and attending board meetings.

In addition to the discussions of the relationship between gender diversity and firm performance, there is also abundant literature on women’s entrepreneurship. Different from scholarly discussions of gender diversity and firm performance that emphasize the direction of the relationship, studies that focus on gender and entrepreneurship evaluate more closely the variety of factors that impact women in an entrepreneurial setting and their resulting impacts. For instance, topics in this literature include the exploration of gender and entrepreneurs' motivations and success (Marlow and McAdam, 2013; Rocha and van Praang, 2020) as well as gendered challenges to business growth (Brush et al., 2017).

2.2 Gender diversity and innovation

Research on innovation has flourished for the past few decades. In particular, scholarly discussions on innovation performance summarizes the impact of the innovation activities and the organization’s ability to adopt and implement new ideas, processes, or products successfully.

The majority of scholarly discussions on innovation focus on products, processes, or organizations as well as its relationship to a firm’s financial concerns such as merger and acquisition strategy (Bena and Li, 2014) and stock liquidity (Fang et al., 2014). However, studies on innovation seldom pay attention to gender diversity and dynamics. Similarly, although innovation is an important intermediate firm outcome and a counterpart to entrepreneurship, studies on gender diversity and its impact on firm value do not put innovation at the core of their inquiry despite the abundant literature on gender diversity and firm performance and entrepreneurship (Brush et al., 2022). As a result, we have a narrow understanding of the gender dimension in innovation and how a feminine perspective may contribute to research on innovation (Pecis and Berglund, 2021).

Extant literature on gender and innovation explores and emphasizes the unique perspective that women on management teams, R&D teams, and boards of directors contribute to their firm’s innovation performance and capability (Brush et al., 2022). For instance, Foss et al. (2022) highlight a positive association between women managers and firm innovation in a cross-country setting. They also point out that women managers in countries with voluntary or entirely absent gender quotas are predominantly selected on the basis of their qualifications. On the other hand, Díaz-García et al. (2013) find that gender diversity within R&D teams fosters novel solutions leading to radical innovation and Ruiz-Jiménez et al. (2014) demonstrate a similar relationship between women in top management teams and organizations’ innovative performance in technology-based firms in Spain. Nevertheless, this relationship was seldomly evaluated for women in leading executive positions for companies in North America. Thus, this paper hopes to first solidify the positive relationship between gender diversity in executive teams and the firm’s innovation performance in the U.S. where there is limited gender quota and managers and top chief executives are selected based on performance.

*Hypothesis a: There is a positive contemporaneous correlation between gender diversity in top executive positions and their firm’s innovation performance in the U.S.*

Additionally, while existing research focuses on the impact of women in different levels and positions on innovation, there is a scarcity of research that studies the differences of this impact in different industries despite similar studies being carried out in prior scholarly discussion that focus on the relationship between gender diversity and firm performance instead. In particular, Mohsni and Shata (2021) find that the effect of board gender diversity on performance is positive and strongest in Consumer Staples, Utilities, and Real Estate, and negative and significant in Industrials in Canada. As a result, this paper also hopes to answer the following:

*Hypothesis b: There is a difference in the correlation between gender diversity in top executive positions and their firm’s innovation performance from industry to industry in the U.S.*

**3. Data**

3.1 Data Sources

This paper will construct a specific panel database on U.S. patents and the gender diversity of firm executives utilizing data from other available online databases. First, I would use the National Bureau of Economic Research (NBER) patent database which includes detailed information on patents submitted to the U.S. Patent and Trademark Office (USPTO) from 1976 to 2006. I would supplement this data with USPTO’s patent database, PatentsView, to obtain the exact year of the patent assignments. Then, I would merge the patent data with data on S&P 1500 companies and their executives using Wharton Research Data Services’ (WRDS) COMPUSTAT EXECUCOMP and identify the industries for the patents and companies based on the Standard Industrial Classification (SIC) Code List. Specific attention would be paid to the aggregate 2-digits SIC industries. One thing to note is that EXECUCOMP data dates only back to as early as 1992, so this paper would restrict the year range of data from 1992 to 2006 for the two databases when merged and would eliminate firms without paired patent data due to the merging.

For the choice of patent database, other patent related studies such as Barbre and Diestre (2022), Ganco et al. (2020), and Harhoff et al. (2016) have solely used patent databases such as USPTO’s PatentsView, Harvard’s Patent Network Dataverse, and European Patent Office’s (EPO) PATSTRAT respectively. However, these databases either do not concern patents assigned in the U.S. or do not facilitate merging with external databases such as COMPUSTAT. As a result, NBER’s patent database with supplements from USPTO’s PatentsView is the most appropriate patent database to use for this study. Indeed, A similar data approach was used by Bernstein (2015) where he merged the NBER patent database with COMPUSTAT to match patents to firms that completed the IPO filing to evaluate whether going public affects innovation.

2.2 Data Description and Analysis

*2.2.1 Key Variables*

**Dependent Variable:** Patenting activity is often regarded and widely accepted as a measurement that reflects the extent of firm innovation (Bernstein, 2015). Most importantly, patent data and information are available for both public and private firms unlike other measurements of innovation such as R&D expenditures which allows this paper to measure and evaluate firm innovation with unbiasedness. This paper will mainly use the count of the number of patents granted to a firm as the measure of its innovation output. Specifically, *PAT\_COUNT* is the dependent variable counting the number of patents in each patent type assigned to firms in any given year between 1992 and 2006. Since filing patents and patent assignment is a choice rather than a random assignment, this leads to unbalance in the data. However, fundamental fixed differences between groups would be eliminated using the methodology explained in the next section.

**Independent Variables:** This paper considers three different measures to capture firms’ gender diversity within top executive positions: 1) *FEM\_PERCENT*: the percentage of female executives in a given year for a given firm; 2) *FEM\_NUM*: the number of female executives in a given year for a given firm; 3) *FEM\_DUM*: a dummy variable which equals 1 if there is at least one female executives in a given year for a given firm or 0 otherwise. These three variables are constructed from the *GENDER\_DUM* variable, a dummy variable that equals 1 if the executive is female and 0 otherwise, which is created from the executive information available at EXECUCOMP. As firms can report anywhere from 5 to 9 executives to EXECUCOMP, the three different independent variables would allow us to assess the relationship between gender diversity in the executive teams and innovation performance more comprehensively, potentially providing more insights into the relationship.

**Control Variables:** There are four main control variables to hold Patent-Level, Individual-Level, and Firm-Level variation constant: 1) *PTYPE*: there are 4 patent types in total (0: Utility, D: Design, R: Reissue, P: Plant); 2) JOINED\_YEAR: the year the executive joined the particular firm; 3) *EMP*: the number of employers in the particular firm in thousands; and 4) *XRD*: Research and Development Expenses in a given year for a given firm in millions of USD. In addition, *GVKEY* and *YEAR* will be used to incorporate Firm-Fixed Effects and Year-Fixed Effects. Altogether, these variables are immutable characteristics of the patents assigned or the companies concerned by this study. They also correlate with both the dependent variable and independent variables and will help holding the confounders fixed for our relationship of interest.

On the other hand, in other to test *Hypothesis b*, the variable *SIC*, which is the 2-digits aggregate industries’ Standard Industrial Classification (SIC) Code, will be used to categorize firms in this dataset into different categories according to SICCODE (2021). Furthermore, a distinction between discrete and complex industries will also be incorporated using the 2-digits SIC code. Cohen et al. (2000) highlights that the key difference between discrete and complex industries is “whether a new, commercializable product or process comprised of numerous separately patentable elements versus relatively few”. In other words, firms in complex industries often do not have proprietary control over all the essential complementary components of at least some of the technologies they are developing. Discrete industries are industries with 2-digits SIC code less than 29 (e.g., food, textiles, chemicals, drugs, metals, and metal products) and complex industries are industries with 3-digits SIC code between 29 and 36 (e.g., machinery, computers, electrical components, and instruments). This distinction will also be used to test *Hypothesis b*.

*2.2.2 Summary Statistics*

Table 1 reports the summary descriptive statistics of the key variables mentioned above except for *SIC* and *PTYPE*. The distribution of the number of patents is significantly right skewed with a big difference of 16.93 between its mean and median. Similar distribution patterns can be identified in the three independent variables where the medians are surprisingly 0 despite means to be greater than 0. This suggests that a lot of the firms do not have a single female executive in a given year. The distributions for *EMP* and XRD are also right skewed, highlighting a wide discrepancy between the average number of employees and research and development expenses and these numbers for the largest firms in terms of employees or research and development efforts. For the control variable *JOINED\_YEAR*, the distribution of the data is slightly left-skewed. This reveals that many of the top executives for the firms in this dataset joined later than 1988 and are relatively younger to the firm. Last but not least, we can see that the control variable *YEAR* appears to be normally distributed with a mean and median near 1998. This tells us that the number of patents did not increase significantly over the range of years this paper concerns.

Table 2 provides additional details on *SIC* and *PTYPE* which are not included in the summary statistics. In particular, Manufacturing with SIC codes ranging from 20-39 occupies the majority of patents assigned, capturing 78.57% of all patents. In addition, the distribution of patents assigned is quite heterogenous across industries. Utility patents and Design patents account for more than 90% of patents assigned for all of the industries except for Public Administration, where they only account for 69.2%. Many of these industries in turn have zero patents assigned in the Reissue and Plant types. Construction has the highest percentage of Utility patents and Retail trade has the highest percentage of Design patents. On the other hand, the distribution of patents assigned is rather relatively homogenous for discrete and complex industries. The differences in percentages across the four patent types only differ for less than 2.3%.

**4. Empirical Methods**

This particular study hopes to validate a relationship between gender diversity and innovation performance but does not seek to establish causation. Indeed, innovation performance is proven to be related and affected by many variables and this study will not be able to account for all of these variations given the dataset. Nonetheless, to capture an exact and precise relationship between gender diversity and innovation performance, this study utilizes a Difference-in-Difference regression with panel data. This would assist in resolving fundamental imbalance within the dataset and would isolate the potential relationship between gender diversity and innovation performance. Particularly, this study employs the Poisson Fixed-Effects model developed by Hausman et al. (1984) for count dependent variables. This methodology was initially applied to determine the relationship between patent count and R&D expenditures while having wider applications for any count data. Given the dependent variable of this study also concerns patent counts, this specific methodology would be the most appropriate to use.

The following regressions will be run to test the relationship between gender diversity and patent count to test *Hypothesis a*:

1. *PAT\_COUNT­ =* α *+* β1*FEM\_PERCENT +* + + *JOINED\_YEAR* + *PTYPE + EMP + XRD*
2. *PAT\_COUNT­ =* α *+* β2*FEM\_NUM +* + + *JOINED\_YEAR* + *PTYPE + EMP + XRD*
3. *PAT\_COUNT­ =* α *+* β3*FEM\_DUM +* + + *JOINED\_YEAR* + *PTYPE + EMP + XRD*

These regressions include Firm-Fixed Effects and Year-Fixed Effects allowing us to evaluate the relationship with multiple time periods for multiple firms. In addition, *PTYPE*, *JOINED\_YEAR*, *EMP, and XRD* are controls that are correlated with our independent variables and dependent variable. According to Table 3, they are also not highly correlated with the independent variables which avoid multicollinearity. For instance, the correlations of *PTYPE* with the three independent variables are -0.027, -0.016, and -0.016 respectively. Similarly, the correlations of *JOINED\_YEAR* with the three independent variables are 0.126, 0.128, and 0.133, correlations of EMP with the three independent variables are -0.058, -0.054, and -0.059, and the correlations of XRD with the three independent variables are -0.032, -0.025, and -0.019. These three variables are added to hold confounders fixed in this study.

Subsequently, these three regressions will be run similarly to test *Hypothesis b* but within each constrained industry group. This will allow a closer examination of the difference of this relationship across industries and whether there are any differences in this relationship between discrete and complex industries.

**5. Results**

5.1 Gender Diversity Trends

Despite an overall increasing awareness in gender diversity issues, the under-representation of women in senior positions, and the increasing number of female executives in several renowned firms, the average number of female executives per firm over the years differ significantly across industries as shown in Figure 1. Largely, the range of this average across the industries increased significantly from 0.25 in 1992 to 1 in 2006 and many industries had a vast increase in the presence of female executives. For example, the largest increase in this average can be seen in the Retail Trade industry, where it increased from 0 in 1992 to 1.2 in 2006. Other industries all experienced several periods of increase then decrease in the 1992-2006 time period.

5.2 Regression Results

*5.2.2 Relationship between gender diversity and innovation performance*

Table 4 identifies the three regressions ran to test *Hypothesis a*. All three regressions, with corresponding p-values of 0.142, 0.121, and 0.120, illustrate no significant relationship between gender diversity in the executive team and innovation performance for our dataset and thus we have to reject our initial hypothesis. There are three mechanisms to this insignificance: 1) the correlation between gender diversity and innovation performance of large publics firms versus smaller firms and ventures; 2) the differences of this correlation between industries; and 3) the correlation between gender diversity and firm performance and its similarity to the correlation between gender diversity and innovation performance.

First, according to Mohsni and Shata (2021), women directors have a higher impact on the performance of smaller firms compared to larger ones and that the smaller firms benefit the most from gender diversity within their boards. Similar results were also found by Li and Chen (2018). They find that board gender diversity has a positive impact on firm performance but this impact becomes negative as the size of the firm increases. These findings can be extended to innovation performance which serves as an intermediary to firm performance (Brush et al., 2022). With our dataset drawn by matching patents assigned in U.S. to COMPUSTAT S&P top 1500 firms, the insignificance of the correlation between gender diversity and patent count can be attributed to the dataset and the effect of firm size.

Inter-industry comparisons provide another justification to the insignificance of the correlation between gender diversity in the executive team and innovation performance. As we will see in the next section, this insignificance can be largely attributed to the different magnitudes and directions of the relationship between gender diversity and innovation performance across industries while incorporating Firm-Fixed Effects and Year-Fixed Effects.

Lastly, parallels can be drawn between gender diversity and innovation performance with gender diversity and firm performance. As mentioned above in Section 2.1, studies provide evidence of no relationship relationship (e.g., Chapple & Humphrey, 2014), a conditional relationship (e.g., Dwyer et al., 2013), or a negative relationship (e.g., Adams and Ferreira, 2009) between gender diversity and firm performance although other studies present evidence of a positive relationship, whether in a different setting, using different datasets, or having other measures of gender diversity such as gender diversity of the board or middle management rather than the executive team. Since innovation performance serves as an intermediary to firm performance (Brush et al., 2022), this mixture of significance and direction of results can be extended to the correlation between gender diversity and innovation performance, as significance and direction of this correlation relies substantially on the context and dataset defined in each study.

Nonetheless, the tests also demonstrate a significance of patent type and executives’ joined year to the number of patent count. Note how in order to control for *PTYPE* in this regression, the initial patent types are transformed to numbers 1-4 representing the four patent types. Specifically, 1 represent Utility, 2 represent Design, 3 represent Reissue, and 4 represent Plant. As we saw earlier in Table 2, the number of patents assigned decreases from Utility to Design to Reissue and to Plant patents. Thus, the significance of PTYPE only indicates the trends in patents assigned for the four categories.

On the other hand, there is a negative but strong correlation between *JOINED\_YEAR* and *PAT\_COUNT*. This suggests that the younger an executive is to the firm, the smaller the number of patents assigned to that firm that year. This may be attributed to the positive relationship between knowledge and innovation performance as the origin of an innovation is found in the knowledge developed or acquired and stored by the firm (Ruiz-Jiménez et al., 2014). As a result, executives who are more experienced and knowledgeable of their firm would positively affect the innovation performance of their firm, and vice versa.

*5.2.3 Inter-industry Comparison*

Tables 5, 6, and 7 present panels of regression results to test *Hypothesis b* with *PAT\_COUNT* as the dependent variables and *FEM\_PERCENT*, *FEM\_NUM*, and *FEM\_DUM* respectively as the independent variables for all the industries listed in Table 2. In general, industries demonstrate no correlation between gender diversity in the executive team and innovation performance except Columns 7, 8, and 11. This reinforces our findings for *Hypothesis a*. However, differences observed in Columns 7 and 11 in particular confirms our *Hypothesis b*, where a difference in the correlation between gender diversity in the executive team and innovation performance exist. Note that columns 1, 3, 6, and 10 are left blank due to the small amount of data points available to construct a panel regression after data on USPTO assigned patents merge with COMPUSTAT data on executives. These columns correspond to the Agriculture, Forestry, and Fishing industry, the Construction industry, the Wholesale Trade industry, and the Public Administration industry. At the same time, the coefficient and standard error details are missing for *XRD* on Column 7 due to the lack of information on research and development expenses for this specific industry.

We can examine that the correlation between gender diversity and innovation performance is not significant across all industries except Retail Trade. Indeed, regression reveals a positive and strong relationship between gender diversity in the executive team for firms in the Retail Trade industry and innovation performance across all measures of gender diversity using the three independent variables, all significant to the 0.001 level. Retail Trade is also the industry with not only the highest number but also the largest increase in the average number of female executives per firm in the 1992–2006 time frame when compared with other industries. However, the industry with the second largest increase in the average number of female executives per firm did not show a similar correlation between gender diversity in the executive team and innovation performance. In fact, Column 8 of Table 5 surprisingly demonstrates a negative correlation between the percentage of female executives and innovation performance for firms in the Finance, Insurance, and Real Estate industry. However, this correlation and its significance demonstrated in Table 5 is invalidated in Column 8 of Table 6 and 7 although the coefficients remain negative, which reject the possibility of a significant and negative correlation in this case.

Discrete industries, on the other hand, have a positive and significant correlation between gender diversity in the executive team and innovation performance as revealed by Column 11 in all of Table 5, 6, and 7 with a significance level of 0.001. Simultaneously, similar correlation in terms of direction and magnitude cannot be observed for Concrete industries. Concrete industries indeed demonstrate no significant correlation between gender diversity in the executive team and innovation performance. This large difference in significance and results of the regression and correlation stems from the fundamental differences in use of patents and patenting reasons between Discrete and Complex industries.

As mentioned in Section 2.2.1, Cohen et al. (2000) points out the fundamental differences between discrete and complex industries is whether a new, commercializable product or process is comprised of numerous separately patentable elements versus relatively few. In particular, patents filed by firms in Discrete industries, such as pharmaceutical companies, are typically new drugs that are comprised of a relatively discrete number of patentable elements, whereas patents filed by firms in Complex industries may comprise hundreds of patentable elements which the firms often do not have proprietary control over. This difference is largely driven the technology and characteristics of a product as well as patent policy.

For firms in the discrete industries, patents are essential and are important means of preserving and sustaining competitive advantages. They only form alliances after strict due diligence and a certain level of mutual trust which leads to fewer number of patent infringement disputes and a larger weight put on the patents. In contrast, patents’ dependence on other patentable elements from a wide range of firms in the Complex industries leads to mutual dependence. One communications equipment manufacturer's executive stated: “Mostly, your patents are used in horse trading. You come together and say, 'Here's our portfolio.' In our industry, things all build on each other. We all overlap on each other's patents. Eventually we come to some agreement: 'You can use ours and we can use yours '’’ (Cohen et al., 2000). This contrast in the formation of alliances and the degree of trust and dependency result in the difference between patenting reasons. In Discrete industries, firms appear to use their patents commonly to block the development of substitutes by rivals, whereas in Complex industries, firms are much more likely to use patents for trading and cross-licensing or to force rivals into negotiations (Cohen et al., 2000). As a result, while patents are used to validate a new and critical innovation for firms in Discrete industries, they are often used more strategically to strengthen market position and alliances for firms in Complex industries. Patents in Discrete industries, therefore, are stronger signals of firms’ innovation performance than patents assigned to firms in Complex industries due to the differences in both the nature of the patents and patenting reasons.

By drawing on these differences, we can also deduce that *PAT\_COUNT* might no longer be an appropriate measure of innovation performance for firms in Complex industries as it only measures a definite number without providing significant insights into the strengths of the patents. A different measure such as the number of citations might be more appropriate to evaluate whether there is a correlation or not.

Nonetheless, it is evident that there is a strong and positive correlation between gender diversity in the executive team and innovation performance for firms in the Retail Trade industry and in Discrete industries. Coefficients on JOINED\_YEAR and PTYPE also mostly harmonize with findings for Hypothesis a, where the significance of the coefficient on PTYPE shows trends of patents assigned across the four patent types and the significance of the coefficient on JOINED\_YEAR suggests how executives who are more experienced and knowledgeable of their firm would positively affect the innovation performance of their firm, and vice versa.

5.3 Robustness Check

* All tests are conducted with robust standard errors clustered at the firm level
* Random effects vs Fixed effects: included Hausman specification test results to confirm the use of fixed effects model
* We next run regressions using panel data models in order to control for unobserved firm heterogeneity that remains constant over the time period we study. Thus we test the validity of the fixed effects estimator by using the Hausman test. The result shows that the Hausman test rejects the random effects estimator and thus fixed effect models are preferred in the paper. The regression results of fixed effect models are reported in the column of Model (1) in Table [**4**](https://onlinelibrary.wiley.com/doi/full/10.1111/beer.12188?saml_referrer#beer12188-tbl-0004). The results indicate that coefficient of gender diversity (*FERAT*) remains positive and statistically significant at the 1% level.

**6. Discussion and Conclusion**

6.1 Results and Implications

6.2 Limitations

* patent litigations in 2006, 2010, and 2014 brought significant changes to the patent system and these changes might impact results if the dataset includes more recent data points
* regressions for Hypothesis b were ran based on SIC code industry categories according to SICCODE. There are definitely other categorizations that have minor differences

6.3 Conclusion and Future Research

* summarize this study’s contribution
* future research:
  + research into specific industries and conduct studies focusing on a specific industry rather than drawing conclusions as a whole
  + evaluate using recent data and see how patent litigations mentioned above brought changes to this relationship, if any

**Tables and Figures**

***Table 1.*** *Summary statistics of key variables*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Mean | Median | Std. Dev. | Min. | Max. |
| ***PAT\_COUNT*** | 20.93 | 4 | 90.04 | 1 | 4106 |
| ***FEM\_PERCENT (%)*** | 3.92% | 0% | 0.09 | 0% | 100% |
| ***FEM\_NUM*** | 0.24 | 0 | 0.53 | 0 | 5 |
| ***FEM\_DUM*** | 0.20 | 0 | 0.40 | 0 | 1 |
| ***YEAR*** | 1998.43 | 1998 | 3.78 | 1992 | 2006 |
| ***JOINED\_YEAR*** | 1988.41 | 1992 | 12.06 | 1946 | 2006 |
| ***EMP*** | 20.90 | 5.60 | 54.07 | 0.005 | 1500 |
| ***XRD*** | 165.26 | 14.67 | 626.67 | 0 | 12183 |

***Table 2.*** *List of ranges of SIC codes, their respective industries, the composition of patent types within each range, and the number of total patents across different SIC code ranges*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Patent Type (%) | | | |  |
| SIC | Industry | Utility | Design | Reissue | Plant | Total |
| 01-09 | Agriculture, Forestry, & Fishing | 81.579 | 10.526 | 5.263 | 2.632 | 38 |
| 10-14 | Mining | 91.942 | 2.930 | 5.128 | 0 | 273 |
| 15-17 | Construction | 96.667 | 3.333 | 0 | 0 | 30 |
| 20-39 | Manufacturing | 72.122 | 23.022 | 4.827 | 0.029 | 7,002 |
| 40-49 | Transportation & Public Utilities | 86.220 | 12.205 | 1.575 | 0 | 254 |
| 50-51 | Wholesale Trade | 79.121 | 20.879 | 0 | 0 | 91 |
| 52-59 | Retail Trade | 53.676 | 46.324 | 0 | 0 | 136 |
| 60-67 | Finance, Insurance, & Real Estate | 85.628 | 10.180 | 4.192 | 0 | 167 |
| 70-89 | Services | 88.723 | 8.976 | 2.186 | 0.115 | 869 |
| 91-99 | Public Administration | 34.615 | 34.615 | 30.770 | 0 | 52 |
| 01-28 | Discrete | 75.107 | 19.983 | 4.782 | 0.128 | 2342 |
| 29-36 | Complex | 72.907 | 22.189 | 4.904 | 0 | 3344 |
| Note: The % across four Patent Types add up to 100% for each range (row) of SIC codes. | | | | | | |

***Table 3.*** *Pearson Correlation Matrix*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **PAT\_ COUNT** | **FEM\_ PERCENT** | **FEM\_ NUM** | **FEM\_ DUM** | **YEAR** | **JOINED\_ YEAR** | **PTYPE** | **EMP** | **XRD** |
| **PAT\_COUNT** | 1.000 |  |  |  |  |  |  |  |  |
| **FEM\_PERCENT** | -0.032 | 1.000 |  |  |  |  |  |  |  |
| **FEM\_NUM** | -0.025 | 0.964 | 1.000 |  |  |  |  |  |  |
| **FEM\_DUM** | -0.029 | 0.923 | 0.932 | 1.000 |  |  |  |  |  |
| **YEAR** | -0.022 | 0.157 | 0.154 | 0.159 | 1.000 |  |  |  |  |
| **JOINED\_YEAR** | -0.084 | 0.126 | 0.128 | 0.133 | 0.420 | 1.000 |  |  |  |
| **PTYPE** | -0.089 | -0.027 | -0.016 | -0.016 | -0.077 | -0.164 | 1.000 |  |  |
| **EMP** | 0.161 | -0.058 | -0.054 | -0.059 | 0.008 | -0.159 | 0.179 | 1.000 |  |
| **XRD** | 0.255 | -0.032 | -0.025 | -0.019 | 0.086 | -0.126 | 0.241 | 0.465 | 1.000 |

***Table 4.*** *Relationship between gender diversity and innovation performance*

|  |  |  |  |
| --- | --- | --- | --- |
| DV: Patent Count | | | |
|  | **1** | **2** | **3** |
| *IV* | 0.6664  (0.4539) | 0.1017  (0.0657) | 0.1512  (0.0973) |
| *JOINED\_YEAR* | -0.0065\*\*  (0.0032) | -0.0064\*\*  (0.002) | -0.0067\*\*  (0.0032) |
| *PTYPE* | -2.6246\*\*\*  (0.2090) | -2.6240\*\*\*  (0.2092) | -2.6238\*\*\*  (0.2086) |
| *EMP* | 0.0018  (0.0011) | 0.0018  (0.0011) | 0.0018  (0.0011) |
| *XRD* | 0.0001  (0.0001) | 0.0001  (0.0001) | 0.0001  (0.0001) |
| # Of Observations | 2511 | 2511 | 2511 |
| # Of Firms | 563 | 563 | 563 |
| Firm-Fixed Effects | Yes | Yes | Yes |
| Year-Fixed Effects | Yes | Yes | Yes |
| Hausman Test | 0.0000 | 0.0000 | 0.0000 |
| Note: 1. FEM\_PERCENT; 2. FEM\_NUM; 3. FEM\_DUM.  Robust standard errors (clustered at the firm level) are reported in parentheses.  \*\*\* p<0.01. \*\* p<0.05. \* p<0.10. | | | |

***Table 5.*** *FEM\_PERCENT vs. PAT\_COUNT across industries*

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| DV: Patent Count | | | | | | | | | | | | |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
| *IV* |  | 1.9596  (1.4794) |  | 0.4555  (0.4910) | 9.2994  (5.0279) |  | 5.3969\*\*\*  (6.08x10-11) | -28.9447\*\*\*  (5.0821) | -0.6908  (0.8504) |  | 2.1184\*\*\*  (0.7806) | -0.0646  (0.9874) |
| *JOINED\_ YEAR* |  | -0.0101  (0.0064) |  | -0.0091\*\*\*  (0.0032) | -0.1298\*  (0.0687) |  | -0.1300\*\*\*  (3.14x10-13) | -0.2595\*\*\*  (0.1314) | -0.0074  (0.0192) |  | -0.0086\*\*  (0.0037) | -0.0079\*\*\*  (0.0026) |
| *PTYPE* |  | -2.3499\*\*\*  (0.2266) |  | -2.4110\*\*\*  (0.1984) | -1.3922\*\*\*  (0.1297) |  | -0.4713\*\*\*  (5.38x10-12) | -0.9762\*\*\*  (0.4865) | -2.9988\*\*\*  (0.7638) |  | -2.2485\*\*\*  (0.2205) | -2.3760\*\*\*  (0.2666) |
| *EMP* |  | 0.0340\*\*  (0.0159) |  | 0.0021  (0.0013) | 0.1047\*\*\*  (0.0152) |  | 0.1291  (1.62x10-14) | 3.6117\*\*\*  (0.4452) | 0.0058  (0.0455) |  | 0.0188\*\*\*  (0.0057) | 0.0187\*\*\*  (0.0031) |
| *XRD* |  | -0.0016  (0.0054) |  | 0.0002  (0.0001) | -0.0059\*\*\*  (0.0009) |  |  | -0.0920\*\*\*  (0.0117) | 0.0008  (0.0009) |  | 0.0001\*  (8.22x10-5) | 0.0004\*\*\*  (0.0001) |
| # Of Observations |  | 43 |  | 2065 | 22 |  | 20 | 24 | 283 |  | 614 | 998 |
| # Of Firms |  | 9 |  | 456 | 6 |  | 6 | 6 | 67 |  | 128 | 211 |
| Firm-Fixed Effects |  | Yes |  | Yes | Yes |  | Yes | Yes | Yes |  | Yes | Yes |
| Year-Fixed Effects |  | Yes |  | Yes | Yes |  | Yes | Yes | Yes |  | Yes | Yes |
| Hausman Test |  | 0.0000 |  | 0.0000 | 0.0000 |  | 0.0000 | 0.0000 | 0.0000 |  | 0.0000 | 0.0000 |
| Note: 1-12 are different SIC industry groups: 1. Agriculture, Forestry, & Fishing; 2 Mining; 3. Construction; 4. Manufacturing; 5. Transportation & Public Utilities; 6. Wholesale Trade; 7. Retail Trade; 8. Finance, Insurance, & Real Estate; 9. Services; 10. Public Administration; 11. Discrete Industries; and 12. Complex Industries.  Robust standard errors (clustered at the firm level) are reported in parentheses.  \*\*\* p<0.01. \*\* p<0.05. \* p<0.10. | | | | | | | | | | | | |

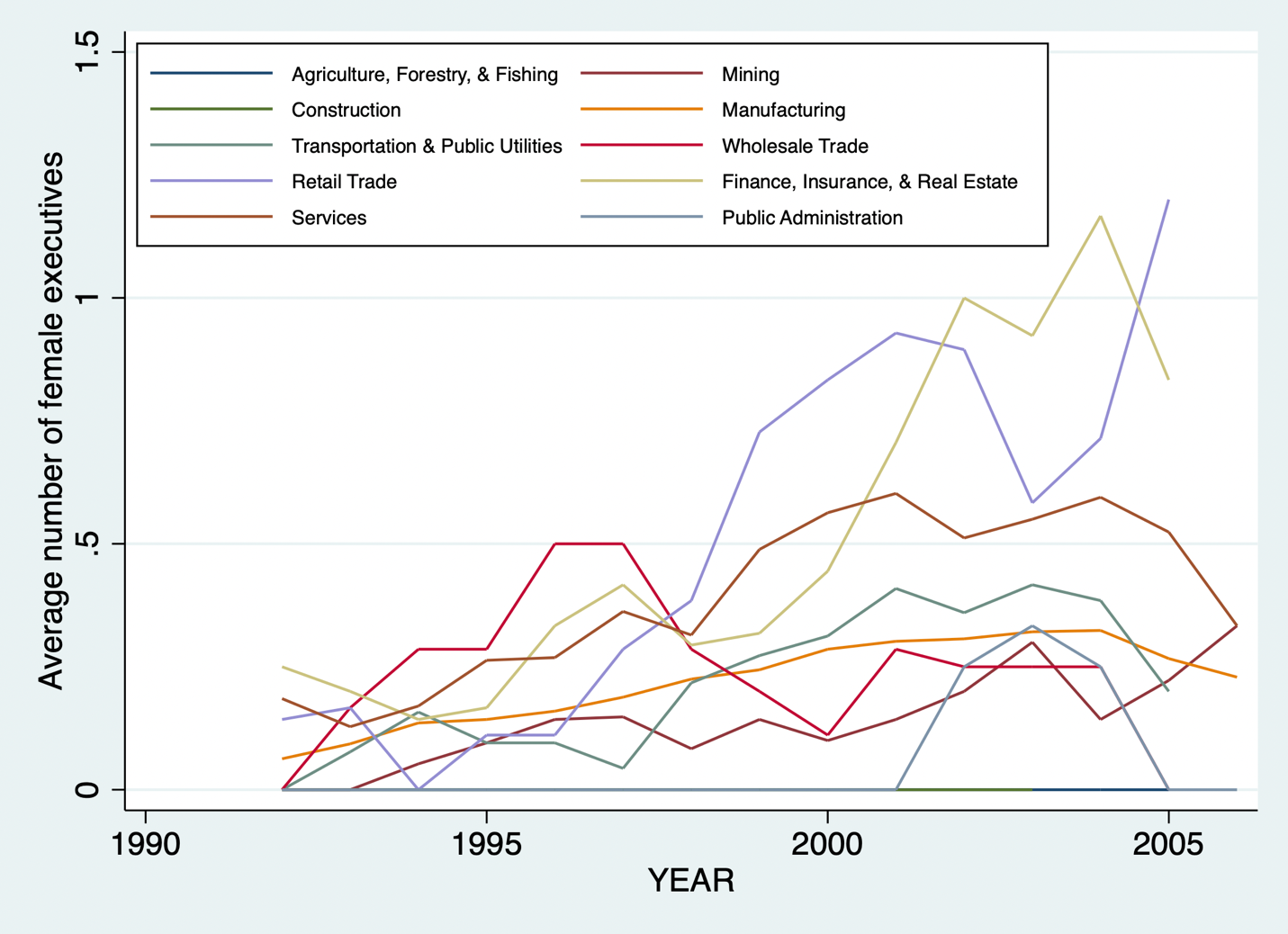
***Table 6.*** *FEM\_NUM vs. PAT\_COUNT across industries*

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| DV: Patent Count | | | | | | | | | | | | |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
| *IV* |  | 0.1847  (0.2643) |  | 0.0655  (0.0681) | 0.8864  (0.6000) |  | 0.6746\*\*\*  (9.08x10-12) | -3.0473  (2.6570) | -0.0095  (0.1357) |  | 0.3019\*\*\*  (0.1225) | 0.0079  (0.1333) |
| *JOINED\_ YEAR* |  | -0.0117\*  (0.0065) |  | -0.0089\*\*\*  (0.0032) | -0.0838\*\*  (0.0379) |  | -0.1300\*\*\*  (3.70x10-13) | -0.2523  (0.1883) | -0.0076  (0.0199) |  | -0.0082\*\*  (0.0037) | -0.0079\*\*\*  (0.0027) |
| *PTYPE* |  | -2.3933\*\*\*  (0.2324) |  | -2.4108\*\*\*  (0.1987) | -1.2432\*\*\*  (0.0974) |  | -0.4713\*\*\*  (6.44x10-12) | -1.0574  (0.6672) | -3.0045\*\*\*  (0.7665) |  | -2.2479\*\*\*  (0.2192) | -2.3745\*\*\*  (0.2663) |
| *EMP* |  | 0.0350\*\*  (0.1711) |  | 0.0021\*\*\*  (0.0013) | 0.0872\*\*\*  (0.0031) |  | 0.1291  (1.97x10-14) | 2.3477\*\*  (1.1347) | 0.0080  (0.0177) |  | 0.01827\*\*\*  (0.0059) | 0.0087\*\*\*  (0.0031) |
| *XRD* |  | -0.0013  (0.0058) |  | 0.0002  (0.0001) | -0.0051\*\*\*  (0.0012) |  |  | -0.0492\*\*  (0.0212) | 0.0008  (0.0009) |  | 0.0001  (0.0001) | 0.0004\*\*  (0.0001) |
| # Of Observations |  | 43 |  | 2065 | 22 |  | 20 | 24 | 283 |  | 614 | 998 |
| # Of Firms |  | 9 |  | 456 | 6 |  | 6 | 6 | 67 |  | 128 | 211 |
| Firm-Fixed Effects |  | Yes |  | Yes | Yes |  | Yes | Yes | Yes |  | Yes | Yes |
| Year-Fixed Effects |  | Yes |  | Yes | Yes |  | Yes | Yes | Yes |  | Yes | Yes |
| Hausman Test |  | 0.0000 |  | 0.0000 | 0.0000 |  | 0.0000 | 0.0000 | 0.0000 |  | 0.0000 | 0.0000 |
| Note: 1-12 are different SIC industry groups: 1. Agriculture, Forestry, & Fishing; 2 Mining; 3. Construction; 4. Manufacturing; 5. Transportation & Public Utilities; 6. Wholesale Trade; 7. Retail Trade; 8. Finance, Insurance, & Real Estate; 9. Services; 10. Public Administration; 11. Discrete Industries; and 12. Complex Industries.  Robust standard errors (clustered at the firm level) are reported in parentheses.  \*\*\* p<0.01. \*\* p<0.05. \* p<0.10. | | | | | | | | | | | | |

***Table 7.*** *FEM\_DUM vs. PAT\_COUNT across industries*

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| DV: Patent Count | | | | | | | | | | | | |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
| *IV* |  | 0.1847  (0.2643) |  | 0.1246  (0.1098) | 0.8864  (0.6002) |  | 0.6746\*\*\*  (9.08x10-12) | -3.0473  (2.6570) | -0.1657  (0.2112) |  | 0.4116\*\*\*  (0.1625) | 0.1083  (0.1887) |
| *JOINED\_ YEAR* |  | -0.0117  (0.0065) |  | -0.0091\*\*\*  (0.0032) | -0.0838\*\*  (0.0379) |  | -0.1300\*\*\*  (3.70x10-13) | -0.2523  (0.1883) | -0.0706  (0.0189) |  | -0.0060  (0.0038) | -0.0079\*\*\*  (0.0025) |
| *PTYPE* |  | -2.3933\*\*\*  (0.2324) |  | -2.4110\*\*\*  (0.1984) | -1.2432\*\*\*  (0.0974) |  | -0.4713\*\*\*  (6.44x10-12) | -1.0574  (0.6672) | -2.9874\*\*\*  (0.7521) |  | -2.3459\*\*\*  (0.2271) | -2.3694\*\*\*  (0.2634) |
| *EMP* |  | 0.0350\*\*  (0.0171) |  | 0.0021  (0.0013) | 0.0872\*\*\*  (0.0196) |  | 0.1291  (1.97x10-14) | 2.3477\*\*  (1.1347) | 0.0085  (0.0454) |  | 0.00162\*\*\*  (0.0055) | 0.0087\*\*\*  (0.0030) |
| *XRD* |  | -0.0013  (0.0058) |  | 0.0002  (0.0001) | -0.0051\*\*\*  (0.0012) |  |  | -0.0492\*\*  (0.0212) | 0.0008  (0.0009) |  | 0.0002\*\*  (0.0001) | 0.0004\*\*\*  (0.0002) |
| # Of Observations |  | 43 |  | 2065 | 22 |  | 20 | 24 | 283 |  | 614 | 998 |
| # Of Firms |  | 9 |  | 456 | 6 |  | 6 | 6 | 67 |  | 128 | 211 |
| Firm-Fixed Effects |  | Yes |  | Yes | Yes |  | Yes | Yes | Yes |  | Yes | Yes |
| Year-Fixed Effects |  | Yes |  | Yes | Yes |  | Yes | Yes | Yes |  | Yes | Yes |
| Hausman Test |  | 0.0000 |  | 0.0000 | 0.0000 |  | 0.0000 | 0.0000 | 0.0000 |  | 0.0000 | 0.0000 |
| Note: 1-12 are different SIC industry groups: 1. Agriculture, Forestry, & Fishing; 2 Mining; 3. Construction; 4. Manufacturing; 5. Transportation & Public Utilities; 6. Wholesale Trade; 7. Retail Trade; 8. Finance, Insurance, & Real Estate; 9. Services; 10. Public Administration; 11. Discrete Industries; and 12. Complex Industries.  Robust standard errors (clustered at the firm level) are reported in parentheses.  \*\*\* p<0.01. \*\* p<0.05. \* p<0.10. | | | | | | | | | | | | |

***Figure 1.*** *Average number of female executives per firm from 1992 to 2006*



**References**

Adams, R. B., & Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics*, *94*(2), 291–309. https://doi.org/  
10.1016/j.jfineco.2008.10.007

Barber, B., & Diestre, L. (2022). Can firms avoid tough patent examiners through examiner-shopping? Strategic timing of citations in USPTO patent applications. *Strategic Management Journal*, *43*(9), 1854–1871. https://doi.org/10.1002/smj.3386

Bena, J., & Li, K. (2014). Corporate Innovations and mergers and acquisitions. *The Journal of Finance*, *69*(5), 1923–1960. https://doi.org/10.1111/jofi.12059

Bernstein, S. (2015). Does going public affect innovation? *The Journal of Finance*, *70*(4), 1365–1403. https://doi.org/10.1111/jofi.12275

Brush, C. G., Eddleston, K. A., Edelman, L. F., Manolova, T. S., McAdam, M., & Rossi‐Lamastra, C. (2022). Catalyzing change: Innovation in women's entrepreneurship. *Strategic Entrepreneurship Journal*, *16*(2), 243–254. https://doi.org/10.1002/sej.1435

Brush, C., Greene, P., Balachandra, L., & Davis, A. (2017). The gender gap in venture capital- progress, problems, and perspectives. *Venture Capital*, *20*(2), 115–136. https://doi.org/  
10.1080/13691066.2017.1349266

Carter, D. A., Simkins, B. J., & Simpson, W. G. (2003). Corporate governance, board diversity, and firm value. *The Financial Review*, *38*(1), 33–53. https://doi.org/10.1111/1540-6288.00034

Chapple, L. & Humphrey, J.E. (2014). Does board gender diversity have a financial impact? Evidence using stock portfolio performance. Journal of Business Ethics, 122(4), 709–723.

Cohen, W., Nelson, R., & Walsh, J. (2000). Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not). https://doi.org/10.3386/  
w7552

Díaz-García, C., González-Moreno, A., & Sáez-Martínez, F. J. (2013). Gender diversity within R&D teams: Its impact on radicalness of Innovation. *Innovation: Management, Policy & Practice*, 2236–2259. https://doi.org/10.5172/impp.2012.2236

Dwyer, S., Richard, O.C., & Chadwick, K. (2003). Gender diversity in management and firm performance: The influence of growth orientation and organizational culture. Journal of Business Research, 56(12), 1009–1019.

Fang, V. W., Tian, X., & Tice, S. (2014). Does stock liquidity enhance or impede firm innovation? *The Journal of Finance*, *69*(5), 2085–2125. https://doi.org/10.1111/jofi.12187

Ferrary, M., & Déo, S. (2022). Gender diversity and firm performance: When diversity at middle management and staff levels matter. *The International Journal of Human Resource Management*, 1–35. https://doi.org/10.1080/09585192.2022.2093121

Foss, N., Lee, P. M., Murtinu, S., & Scalera, V. G. (2022). The XX Factor: Female Managers and innovation in a cross-country setting. *The Leadership Quarterly*, *33*(3), 101537. https://doi.org/10.1016/j.leaqua.2021.101537

Ganco, M., Miller, C. D., & Toh, P. K. (2020). From litigation to innovation: Firms' ability to litigate and technological diversification through human capital. *Strategic Management Journal*, *41*(13), 2436–2473. https://doi.org/10.1002/smj.3203

Garcia, R., & Calantone, R. (2002). A critical look at technological innovation typology and innovativeness terminology: A literature review. *Journal of Product Innovation Management*, *19*(2), 110–132. https://doi.org/10.1111/1540-5885.1920110

Hall, B., Jaffe, A., & Trajtenberg, M. (2001). The NBER Patent Citation Data File: Lessons, insights and Methodological Tools. https://doi.org/10.3386/w8498

Harhoff, D., von Graevenitz, G., & Wagner, S. (2016). Conflict resolution, public goods, and patent thickets. *Management Science*, *62*(3), 704–721. https://doi.org/10.1287/  
mnsc.2015.2152

Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica*, *52*(4), 909–938. https://doi.org/10.2307/1911191

Kelly, J. (2021, December 10). *Women now hold more jobs than men in the U.S. workforce*. Forbes. Retrieved February 5, 2023, from https://www.forbes.com/sites/jackkelly/  
2020/01/13/women-now-hold-more-jobs-than-men/?sh=c8060728f8ac

Li, H., & Chen, P. (2018). Board gender diversity and firm performance: The moderating role of firm size. *Business Ethics: A European Review*, *27*(4), 294–308. https://doi.org/10.1111/  
beer.12188

Marlow, S., & McAdam, M. (2013). Gender and entrepreneurship. *International Journal of Entrepreneurial Behavior & Research*, *19*(1), 114–124. https://doi.org/10.1108/  
13552551311299288

Mohsni, S., & Shata, A. (2021). Board Gender Diversity and Firm Performance: The Role of Firm Size. https://www.hillsdaleinv.com/uploads/Board\_Gender\_Diversity\_and\_  
Firm\_Performance.pdf

Pecis, L., & Berglund, K. (2021). Hidden in the limelight: A feminist engagement with innovation studies. *Organization*, *28*(6), 993–1017. https://doi.org/10.1177/  
13505084211015380

Ramarajan, L., & Thomas, D. A. (2010). A positive approach to studying diversity in organizations. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1674930

Rocha, V., & van Praag, M. (2020). Mind the gap: The role of gender in Entrepreneurial Career Choice and social influence by founders. *Strategic Management Journal*, *41*(5), 841–866. https://doi.org/10.1002/smj.3135

Ruiz-Jiménez, J. M., Fuentes-Fuentes, M. del, & Ruiz-Arroyo, M. (2014). Knowledge combination capability and innovation: The effects of gender diversity on top management teams in technology-based firms. *Journal of Business Ethics*, *135*(3), 503–515. https://doi.org/10.1007/s10551-014-2462-7

SICCODE. (2021). *Sic code lookup: Sic code search tool*. SIC & NAICS Codes, Company Search, Business Lists - SICCODE.com. Retrieved March 31, 2023, from https://siccode.com/sic-code-lookup-directory

Simionescu, L. N., Gherghina, Ş. C., Tawil, H., & Sheikha, Z. (2021). Does board gender diversity affect firm performance? empirical evidence from Standard & Poor’s 500 information technology sector. *Financial Innovation*, *7*(1). https://doi.org/10.1186/s40854-021-00265-x

Terjesen, S., Sealy, R., & Singh, V. (2009). Women directors on corporate boards: A review and research agenda. *Corporate Governance: An International Review*, *17*(3), 320–337. https://doi.org/10.1111/j.1467-8683.2009.00742.x

U.S. Patent and Trademark Office. “Data Download Tables.” PatentsView. Accessed [2023-02-21]. https://patentsview.org/ download/data-download-tables.

Wharton Research Data Services. "WRDS" wrds.wharton.upenn.edu, accessed 2023-02-21.