Top Management Human Capital, Inventor Mobility, and Corporate Innovation

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Abstract

Using panel data on top management characteristics and a management quality factor constructed using common factor analysis on individual management quality proxies, we analyze the relation between the human capital or "quality" of firm management and its innovation inputs and outputs. We control for the endogenous matching between firm and management quality using a plausibly exogenous shock to the supply of new managers as an instrument, thereby finding a causal relationship between management quality and innovation activities. We show that higher management quality firms achieve greater innovation output by hiring more and higher quality inventors.

Keywords: Corporate Innovation; Top Management Human Capital; Inventor Mobility

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1 Introduction

The effectiveness of a firm's top management team in investing and managing innovative projects may determine the long-term success of the firm. Indeed, prior literature suggests that firms' investments in research and development (R&D) and their innovative output (measured by patents and citations) may have a positive impact on the long-term financial health of the firm. Given this, there is surprisingly little analysis into how the human capital or "quality" of the top management team of a firm may impact the firm's innovative output. We aim to fill this gap in the literature.

One strand of theoretical literature suggests that higher quality management teams may invest in long-run value oriented projects (e.g., Chemmanur and Jiao (2012)). Given that innovative projects are among such long-run value enhancing projects (e.g., Hirshleifer, Hsu, and Li (2013) and Griliches (1990)), we expect that higher quality management teams will invest in more innovative projects and will have a greater extent of innovative output, on average. Further, they can accomplish this by having better foresight into the potential value of innovative investment opportunities and by more effectively managing innovative resources such as physical assets (research equipment) and human capital (scientists and inventors). For instance, they may provide an environment that fosters greater failure tolerance in the sense of Manso (2011).[1] Given this, firms with higher quality management teams may attract inventors with greater skills to work for them.

The above arguments lead to several testable predictions. First, firms with higher quality top management teams will invest more in R&D. Second, firms with higher quality management teams will have a greater extent of innovation (measured by the number of patents) and higher quality innovation (measured by total citations and citations per patent). Third, better management of innovative assets by higher quality management teams will be reflected in a higher extent of innovative efficiency (e.g., patents per R&D dollar) for such firms. Fourth, the effect of management team quality on innovative output will be stronger for firms facing financial constraints and for firms in competitive industries. Since such firms are at a disadvantage relative to other firms, the "leg-up" provided by a higher quality top management team will enhance their future prospects more. Finally, firms with higher quality management teams will have a larger net inflow of inventors

[1] An example of this is Google's high-risk R&D venture called Google X. Media articles suggest that "......Google X is the search giant's factory for moonshots, those million-to-one scientific bets that require generous amounts of capital, massive leaps of faith, and a willingness to break things." See, *Inside Google's Secret Labs*, Bloomberg Businessweek, May 22, 2013.

(controlling for R&D expenditures) and will hire higher quality inventors (as measured by their prior track record of citations per patent).

The paucity of academic research in finance and economics on the effect of management quality on innovation may be due to two reasons. First, measuring the human capital of a firm's top management team (which we refer to as management quality) involves subjective notions of what constitutes a higher quality management team. Second, potential endogeneity can confound empirical findings on the relation between management quality and innovation. In particular, there may be endogenous matching between higher quality management teams and higher quality firms. We overcome the first hurdle by creating a management team quality index from various measures used previously in the literature, such as management team size, fraction of managers with MBAs, the average employment- and education-based connections of each manager in the management team, the fraction of members with prior work experience in the top management team, the average number of prior board positions that each manager serves on, and the fraction of managers with PhDs. These measures are adjusted for firm size. We create our index of management quality using common factor analysis of the above-mentioned measures of top management quality and extracting a single "management quality factor."[2]

We overcome the second hurdle related to endogeneity by using an instrumental variable (IV) analysis. In our IV analysis, we exploit the strong correlation between the movement of executives across firms and the number of acquisitions in the industry the firm belongs to. In other words, we instrument for top management quality (as measured by our management quality factor) using a plausibly exogenous shock to the supply of top executives available for hire by a firm, namely, the number of acquisitions in the firm's industry four and five years prior. In doing the above, we broadly follow the methodology of Ewens and Marx (2014), who use a similar instrument in their

[2]Starting with the pioneering work of Becker (1964) and Ben-Porath (1967), the labor economics literature has focused on the human capital of workers. The Becker view is that human capital increases a worker's productivity in all tasks, though possibly differentially in different tasks, organizations, and situations. In the Becker view, although the role of human capital in the production process may be quite complex, we can think of it as representable by a unidimensional measure, such as a worker's stock of knowledge or skills, and this stock is directly part of the production function. When analyzing the human capital of the members of a firm's top management team, our view is that managerial human capital is multidimensional, consisting of many different aspects which we capture using the individual measures we mention here, and collapse into one factor, making use of common factor analysis. Thus, our view of human capital is closer to the view of the social psychologist Howard Gardner (see, e.g., Gardner (1983), and Acemoglu and Autor (2011) for a review). An advantage of such a multidimensional approach is that we are able to capture differences in not only the quantity but also the quality of the human capital of the top management teams across firms.

analysis of the relation between value creation by venture capitalists and executive replacements. Similar to Ewens and Marx (2014), we are motivated to use the above instrument by the fact that potential managers available for hire by a firm often come from established firms in the same industry and may leave such firms as a result of acquisitions.

We analyze the relationship between management quality and firm performance using a panel data set of 4,389 firms covering the period 1999 to 2009. We obtain the biographical data on the top managers of firms from the BoardEx database, patent and citation information from the patent data set created by Kogan, Papanikolaou, Seru, and Stoffman (2012) based on the United States Patent and Trademark Office (USPTO), and inventor information associated with each patent from the U.S. Patent Inventor Database (1975-2010): see Lai, D'Amour, Yu, Sun, and Fleming (2013) for a detailed description of the latter database.

Our empirical results can be summarized as follows. First, we find that higher quality management teams invest more in R&D expenditures, showing that they devote a larger amount of resources (input) toward innovative activities. Second, firms with higher quality management teams have a greater extent of innovation output (measured by the number of patents) and higher quality innovation output (measured by total citations and citations per patent). Further, these effects are economically significant. For instance, a one inter-quartile range increase in management quality increases firm patents by 12.3%. We find similar results when we use individual proxies for management quality (such as team size, education, connections, etc.) rather than our overall management quality factor. Third, we find that firms with higher quality management teams produce more patents and citations per R&D dollar, that is, have greater innovative efficiency (see, e.g., Hershleifer, Hsu, and Li (2013)). Finally, the relation between top management team quality and innovation is stronger for firms in financially constrained industries and for firms in more competitive industries. All the above results on the relation between management quality and corporate innovation are confirmed by our IV analysis making use of the instrument discussed above, thus indicating that management quality has a positive and causal effect on corporate innovation.

We then investigate the mechanisms through which higher quality management teams may foster greater innovation in their firms. We argue that higher quality management teams may provide more resources to R&D, manage R&D resources better, and provide a more failure tolerant climate for inventors to succeed in. This, in turn, may make firms with higher management quality attractive to higher quality inventors. Thus, one way that higher quality management teams may enhance innovation is by hiring more and higher quality inventors to work for the firm. Our fifth result is consistent with this conjecture: we find that firms with higher quality management teams experience greater net inflows of inventors (controlling for R&D expenditures), particularly of higher quality inventors. Inventors are defined to be of higher quality if their record of past citations per patent is above that of the median inventor in our sample. We also find that the average citations per patent of incoming inventors into firms with higher quality management teams is higher than the average citations per patent of outgoing inventors from such firms.

Finally, we examine the nature of innovative strategies undertaken by firms with higher quality management teams. In particular, we analyze whether firms with higher quality management teams engage more in exploratory innovative strategies (where they venture into the development of newer technologies or pursue innovations in areas that are less familiar to the firm) or in exploitative innovative strategies (where they may pursue innovations using more conventional technologies or in areas that are more familiar to the firm). To analyze this, we divide the patents obtained by firms into three categories based on whether their citations fall into the group of patents receiving the highest number (top ten percent) of citations ("highly successful innovations"); no citations at all ("unsuccessful innovations"); or somewhere in between ("moderately successful innovations"). If higher management quality firms are engaged in "exploratory" strategies, which are more risky, we would expect such firms to be associated with a larger number of highly successful and a larger number of quite unsuccessful innovations compared to lower management quality firms. Alternatively, if higher management quality firms are engaged in "exploitative" innovative strategies, we would expect such firms to be associated with more moderately successful innovations compared to those achieved by lower management quality firms. The evidence indicates that higher quality management team firms pursue both exploratory and exploitative strategies: we find that firms with higher quality management teams have a larger number of successful innovations, unsuccessful innovations, and moderately successful innovations. However, the successful innovations increase to a greater extent with management quality compared to unsuccessful and moderately successful innovations.

We contribute to several strands in the literature. First, we contribute to the literature linking managerial quality and talent to firm performance, investments, and financing. For instance, Bertrand and Schoar (2003) study the effect of top managers on a firm's financial and investment policies. They find that manager fixed effects explain some of the heterogeneity in the investment, financial, and organizational practices of firms. Chemmanur, Kong, and Krishnan (2015) relate management quality measures similar to ours to firm stock performance, operating performance, and valuation. They also find that higher quality management teams invest more in R&D expenditures. Unlike them, however, we focus on measures of innovative output, innovative efficiency, and inventor mobility. Further, we add to the above literature by analyzing the mechanisms through which higher quality management teams may increase innovation and by analyzing the nature of the innovative strategies adopted by firms with higher versus lower top management team quality.[3,4,5]

Second, we contribute to the recent literature that has analyzed the determinants of innovation in firms (e.g., Manso (2011), Marx, Strumsky, and Fleming (2009), and Chemmanur, Loutskina, and Tian (2014)) and their impact on firm performance (e.g., Hirshleifer, Hsu, and Li (2013), Gu (2005), Eberhart, Maxwell, and Siddique (2004), Lanjouw and Schankerman (2004), Lerner (1994), and Griliches (1990)). Indeed, an important contribution of this paper is to bridge the evidence provided by the above two broad areas of investigation, thus tying management quality to innovative input and output. Third, we provide the first evidence in the literature suggesting that higher quality managers may enhance innovation by attracting higher quality inventors to work for their firm. Fourth, our evidence suggests that higher quality managers are not simply "buying" innovation through greater R&D expenditures, but obtain a higher extent of innovative output

[3] Our paper is also related to Chemmanur and Paeglis (2005) and Chemmanur, Paeglis, and Simonyan (2009). These papers also make use of a management quality factor based on common factor analysis on some individual proxies of management quality to study the relationship between management quality and IPO characteristics (in the case of the former paper) and SEO characteristics and firm financial policies around the SEO (in the case of the latter paper). In contrast to Chemmanur and Paeglis (2005), who study firms going public, our focus in the current paper is on larger, more established firms and how management quality relates to innovative output, innovative efficiency, and inventor mobility. Further, while the above two papers make use of cross-sectional data hand-collected from IPO and SEO prospectuses respectively, our paper makes use of a large panel data set that allows us to capture the time series variation in management quality as well.

[4] In more distantly related research, Bloom and Van Reenen (2007) use an innovative survey tool to collect management practices data from various countries and show that measures of managerial practice are strongly associated with firm-level productivity, profitability, Tobin's Q, and survival rates. See also Bloom, Eifert, Mahajan, McKenzie, and Roberts (2012), who ran a management field experiment on large textile firms in India, and show that adopting better management practices raised productivity by 17% on average in the first year after the adoption of these practices. Unlike these papers, which study the effects of management practices, our focus here is on the effect of the human capital of top firm management on innovation.

[5] Our paper also indirectly related to the literature on the determinants of CEO's quality and how it affects firm performance (see, e.g., Adams, Almeida, and Ferreira (2005) and Malmendier and Tate (2005)). See also Kaplan, Klebanov, and Sorensen (2012), who study the individual characteristics of CEO candidates for companies involved in buyout and venture capital transactions and relate them to the subsequent performance of their companies.

per R&D dollar (higher "bang for the R&D buck"). Finally, we are the first in the literature to demonstrate a casual relation between management quality and innovation.

Two important papers in the economics literature that have implications for our paper are Sah and Stiglitz (1986, 1991). Their theoretical analysis implies that larger management teams are more likely to reject bad projects, since a project will be accepted only if several group members agree that it is good. One of the implications of their theory is that performance should be less variable when a greater number of executives have influence over corporate decisions.[6] Finally, our paper is also related to the growing literature in organizational economics linking the importance of agents across and within organizations. For example, Bandiera, Barankay, and Rasul (2010) find that workers are more productive when they work with higher ability co-workers and less productive when they work with lower ability co-workers (see also Bandiera, Barankay, and Rasul (2005)).[7]

The rest of the paper is organized as follows. Section 2 discusses the underlying theory and develops testable hypotheses. Section 3 outlines the data and the sample selection procedure. Section 4 provides a discussion of our empirical results. Section 5 investigates possible underlying mechanisms. Section 6 presents a discussion of our robustness test results. Section 7 concludes.

2 Theory and Hypothesis Development

In this section, we briefly discuss the underlying theory and develop hypotheses for our empirical tests. Our theoretical motivation partially follows Chemmanur and Jiao (2012), who study a setting in which managers with greater talent or ability are able to create greater long-run cash flows by undertaking long-term projects. However, since their talent is private information, and, since short-term projects come to fruition earlier, myopia or short-termism induced by the stock market (for example, due to the possibility of rivals appearing and successfully taking over the firm in the absence of favorable signals of project success in the short run) impose pressures on them to undertake short-term rather than long-term projects (see also Stein (1988) for another model of corporate myopia). However, more capable managers also have an incentive to undertake long-run

[6]The organizational behavior literature on the effect of managerial discretion on firm performance is also indirectly related to our paper: see Finkelstein and Hambrick (1996) for a review.

[7]In a somewhat different context, Chevalier and Ellison (1999) study the relationship between the performance of mutual funds and the characteristics (age, experience, education and Scholastic Aptitude Test (SAT) scores) of their fund managers. They find that managers who attended higher-SAT undergraduate institutions had significantly higher risk-adjusted excess returns.

rather than short-run projects, since they are able to create greater long-run value by doing so. In such a setting, the equity market prices the equity of firms undertaking long-term projects at a discount, since they are not able to fully observe true managerial ability; however, firms with managers having a higher perceived quality (i.e., with a greater reputation for ability) suffer only a smaller valuation discount if they undertake long-term projects. In summary, managers' choice between long-term and short-term projects is driven by the trade-off between the pressures induced by a myopic stock market versus the ability (and desire) of more able managers to create greater value in the long-run by undertaking long-term projects.[8] Given that innovative projects are long-term projects characterized by short-term failures and experimentation (that increases the gestation time of these projects), managers with greater perceived ability will undertake a greater proportion of long-term (innovative) projects.[9]

The above theoretical framework provides us with our first set of testable implications. First, top management teams with higher (perceived) quality are likely to devote a greater amount of resources to innovation activities. Thus, firms with higher quality management teams will be characterized by larger R&D expenditures, i.e., a larger input of their resources into innovation activities. This is the first hypothesis (**H1**) that we test here. Further, we would expect such firms to be characterized by greater innovation output and higher quality innovation output (after controlling for R&D expenditures). This is the second hypothesis (**H2**) that we test there. Such firms will also be characterized by greater innovative efficiency (i.e., greater innovation output and higher quality innovation output per dollar of R&D capital investment). This is the third hypothesis (**H3**) that we test here.

We also test whether the relationship between management quality and innovation productivity is stronger in some industries than in others. First, consider firms in financially constrained in-

[8]Formally, in Chemmanur and Jiao (2012), the objective function of the manager is a weighted average of the short-run and long-run stock price. Thus, while talented (higher ability) managers will suffer a discount in the firm's short-run stock valuation if they take a greater proportion of long-term projects (since their equity will be priced in a pooling equilibrium with firms with less talented managers), more talented managers have an incentive to undertake a greater proportion of long-term projects since these projects allow them to create greater long-run value and thereby a higher long-run stock price.

[9]Note that, while the true quality of firm management may be private information, the management quality as perceived by outsiders (captured by our management quality measures) affects managers' choice of the proportion of innovative (long-term) projects to undertake. This is because, for managers with higher perceived quality (i.e., with a greater reputation for being talented), the cost of undertaking long-term projects (arising from a firm valuation discount in the short run) will be smaller, leading them to undertake a larger proportion of long-term (innovative) projects.

dustries. Given their financial constraints, such firms will have only a limited amount of resources to devote to innovation. If the relation between management quality and innovation is partly driven by more effective resource management on the part of higher management quality firms, we would expect the relationship between management quality and innovation to be stronger for firms in financially constrained industries (**H4**).[10] Next, consider firms in more competitive versus less competitive industries. Scientists and engineers (inventors) in more competitive industries are likely to have greater outside employment opportunities, so that the talented inventors are likely to be in limited supply in these industries. Therefore, since firms with higher quality management teams are able to attract a greater proportion of these talented inventors in limited supply, we would expect that the relationship between management quality and innovation productivity to be stronger in more competitive industries (**H5**).

We now analyze the channels through which firms with higher management quality are able to generate greater innovation productivity (i.e., greater innovation output for a given amount of resources devoted to R&D expenditures). Consistent with our conjecture that higher quality management teams may be able to manage their innovative activities more efficiently, we hypothesize that firms with higher quality management teams are able to hire more inventors for a given amount of R&D expenditures (**H6**). We further conjecture that firms with higher quality management teams are likely to hire higher quality inventors, who are more innovative (as measured by their prior track record of citations per patent).[11] This is the next hypothesis that we test here (**H7**).

We now delve deeper into the possible differences in the innovation strategies adopted by firms with higher versus lower management quality. One possibility is that higher management quality firms engage in more exploratory innovation strategies (in the sense of Manso (2011)), so that they venture into the development of newer technologies or pursue innovation in areas less familiar to the

[10] The idea here is that, while firms in financially unconstrained industries may be able to partially compensate for not having higher quality management teams by devoting more resources to innovative activities (for example, by buying higher quality equipment), firms in financially constrained industries will be less able to do so, so that the relationship between management quality and innovation will be stronger for the latter category of firms.

[11] For instance, one way in which firms with higher quality management teams may be able to attract higher quality inventors is by promoting a more failure tolerant work environment (in the sense of Manso (2011)). Manso (2011) has argued that an important variable in encouraging innovation is failure tolerance. While Manso (2011) does not distinguish between higher and lower quality firm management teams, if we add the additional assumption that higher quality managers are also more failure tolerant, then it will be the case that firms that have higher quality management teams will also have a more failure tolerant work environment (more conducive to innovative activities).

firm. Given that such an exploratory strategy is more risky, under this scenario we would expect higher management quality firms to be associated with a larger number of highly successful and a larger number of quite unsuccessful innovations (as measured by citations per patent) compared to lower management quality firms: in other words, in this case higher management quality firms will have a larger number of patents in the two tails of the patent quality distribution **(H8A)**. Alternatively, higher management quality firms may engage more in "exploitative" innovative strategies (also in the sense of Manso (2011)), implying that they pursue innovations using more conventional technologies or in areas that are more familiar to the firm. Under the latter scenario, we would expect firms with higher management quality to be associated with more moderately successful innovations (again measured by citations per patent) compared to those achieved by lower management quality firms (**H8B**).[12]

3 Data and Sample Selection

3.1 Sample Selection

Our sample is derived from multiple data sources. Our primary data source of the biographical information of senior managers is the BoardEx database. The BoardEx database contains data on college education, graduate education, past employment history (including beginning and ending dates of various roles), current employment status (including primary employment and outside roles) and social activities (including memberships, positions held in various foundations and charitable groups, etc.). The main information we are making use of in this paper is education, employment history, and demographic information. We collect firm-year patent and citation information from the the patent data set created by Kogan, Papanikolaou, Seru, and Stoffman (2012) (henceforth KPSS). We collect the inventor information associated with each patent from the U.S. Patent Inventor Database (1975-2010) (see Lai, D'Armour, Yu, Sun, and Fleming (2013)). To calculate control variables, we collect financial statement items from Compustat and stock price information from CRSP.

The unique company-level identification code in BoardEx is "Company ID", which is unique

[12]It is difficult to predict from *a priori* theoretical considerations which of the above two scenarios will be realized in practice. We will therefore leave this question to be resolved empirically.

to BoardEx and cannot be used to merge with other databases such as Compustat and CRSP. We link the BoardEx database to Compustat and CRSP in the following way. BoardEx provides CIK, the International Security Identification Number (ISIN) and the company name. The "Company ID" in BoardEx is matched with the PERMNO in CRSP by either CIK or CUSIP (which is derived from ISIN). After matching by CIK or CUSIP, we check the accuracy of the matches by comparing the company name from BoardEx with company names from CRSP and Compustat.

The KPSS patent data set provides detailed data for all patents that are granted by United States Patent and Trademark Office (USPTO) over 1926-2011. We use the KPSS patent data rather than NBER patent data, because the KPSS patent data enable us to identify comprehensive patent portfolios of the firms that filed application up to 2009, which are granted up to 2011. The NBER patent data contain patents that have been granted up to 2006 and most of them had application dates up to 2004. Since our BoardEx sample starts from 1999, using the KPSS patent data increases our sample size significantly.[13] The KPSS patent data provides PERMNO for the assignees of each patent. We use this to merge the patent data with BoardEx as well as Compustat and CRSP. In the base case analysis, we assign zero patents to firms in the BoardEx sample without any patenting activity. The final BoardEx-KPSS Patent-Compustat-CRSP merged file leaves us with 6,504 unique firms.

Using the BoardEx employment history file, we identify all the managers in each matched company for each year from 1999 to 2009. We obtain the sample of senior managers from BoardEx, which we define as managers with a title of VP or higher. The senior managers in our sample can be broadly categorized in seven groups: CEOs, presidents, chairmen, other chief officers (CFO, CIO, etc.), division heads, VPs, and others. We exclude all firm-years that have the following characteristics: (i) there is only one manager in the management team (since it is unlikely that large firms covered by BoardEx have only one senior manager); (ii) there is no CEO for a firm in a certain year; (iii) there are more than 30 senior managers in the management team (suggesting that perhaps certain titles are misleading and we are overclassifying senior managers); (iv) financial and utility firms, defined by SIC code from 6000 to 6999 and from 4901 to 4999, respectively; and (v) firm-years with missing values for the relevant variables that we need to use. After these exclusions,

[13] Although BoardEx data starts from 1997, data prior to 1999 is sparse (e.g., see Engelberg, Gao and Parsons (2013)).

we are left with 30,432 firm-year observations for 4,389 firms.

We then obtain the demographic and education information for each senior manager from the BoardEx database. To obtain education-based connections, we classify all the graduate degrees into four different categories: business school (MBAs included), medical school, law school and other graduate (see, Cohen, Frazzini, and Malloy (2008)).

3.2 Measures of Management Quality

For each management team in each year, we obtain the following seven different measures as proxies for management quality (see, e.g., Chemmanur and Paeglis (2005)):

Team Size: The number of senior managers in the management team.

MBA: The fraction of senior managers in the management team that have MBA degrees.

Prior Work Experience: The fraction of senior managers in the management team that previously worked as senior managers (i.e., VP or higher) in other firms..

Education Connections: The number of education-based connections of the top management team divided by *Team Size*. Education-based connection is total the number of graduate education connections that each senior manager in the management team has with other managers or directors in the BoardEx database. If individuals study in the same educational institutions, have degrees in the same education category (described above), and graduate within one year of each other, they are defined as connected.

Employment Connections: The number of employment connections of the top management team divided by *Team Size*. Employment-based connection is the total number of employment connections that each senior manager in the management team has with other managers or directors in the BoardEx database. If individuals have worked together in the same company previously during an overlapping time period, they are defined as connected.

Prior Board Experience: The total number of outside boards that the top management team members have sat on prior to the current year divided by *Team Size*.

PhD: The fraction of senior managers in the management team that have PhD degrees.

These variables measure management resources, by which we mean the human capital and knowledge resources (including education and related work experience) available to firm management. In addition, we create *Average Tenure* as the the average number of years that each manager has worked in a firm and use it as a control variable.

Table 1 provides summary statistics on the management quality measures that we describe above. For the median firm in our sample, there are seven senior managers in the management team; 20 percent of the senior management team has an MBA degree; 10 percent of the senior management team has prior work experience as a senior manager at another firm; zero percent of the senior management team have sat on boards of other firms; and zero percent of the senior management team has a PhD degree. The median level of *Education Connections* is zero and that of *Employment Connections* is 15.4. The median number of years that each manager has worked in a firm is 5.2 years.

All the management quality measures are aggregated to the level of management team, and are likely to be correlated with firm size. Therefore, in order to ensure these measures are independent of firm size, we use firm size- and industry-adjusted variables in our common factor analysis. Specifically, we estimate the following regression for each of the seven measures of management quality:

$$Measure_{i,t} = \alpha[Ln(firm\ size)_{i,t}] + \beta[Ln(firm\ size)_{i,t}]^2 + Industry\ dummies + Year\ dummies + \epsilon_{i,t} \tag{1}$$

where i indexes the firm and t indexes the year of the observation. *Industry dummies* and *Year dummies* capture industry (defined at 2-digit SIC code level) and year fixed effects, respectively. We use the residuals from the above regression as the firm size- and industry-adjusted measures of the management quality.

Each of the variables described above is likely to have its unique limitations as a measure of the underlying unobservable construct, and is therefore unlikely to be a comprehensive measure of the management quality by itself. Therefore, we use common factor analysis to capture the variation common to our seven observable measures of management quality. More precisely, the aim of our factor analysis is to account for, or explain, the matrix of covariances between our individual management quality measures using as few factors as possible. Next, we rotate the initial factors so that each individual management quality measure has substantial loadings on as few factors as possible. This methodology is consistent with the implementation of the common factor analysis in the literature.[14]

Table 2 presents the results of the common factor analysis. The common factor analysis leads to seven factors. Panel A of Table 2 reports the eigenvalues of each factor. Factors with higher eigenvalues account for a greater proportion of the variance of the observed variables. Only the first factor has an eigenvalue that is greater than one. This suggests that the first factor is the most important, providing us with a distinct measure of management quality. We term this factor the management quality factor (MQF).[15]

Panel B reports the loadings on the first factor for each individual management quality variable. The loadings indicate that all individual management quality measures load positively on the first factor. Consistent with this, the second column of Panel B finds positive correlations between the first factor and each of the seven management quality measures. The third column of Panel B of Table 2 reports the communality of each variable with the common factor, which measures the proportion of the variance of each variable that is accounted for by the common factors. Communality is bounded between zero and one, and higher values indicate that a larger proportion of the variation in the variable is captured by the common factors.

3.3 Measures of Innovation

Following the existing literature (e.g., Kogan, Papanikolaou, Seru, and Stoffman (2012); Seru (2014)) we use patent-based metrics to capture firm innovativeness. While we also use R&D expenditures as a measure of investments in innovative activity, patent-based measures are widely-used proxies of innovation output. We obtain patent data from the database created by KPSS. This database provides detailed information of more than six million patents granted by the USPTO from 1926 to 2011. KPSS have matched assignees in the patent data set with CRSP PERMNOs if the assignee is a public corporation or subsidiary of a public corporation.

[14]We adopt common factor analysis rather than principal component analysis as our method of choice for identifying a single management quality factor. The aim of common factor analysis is to account for or to "explain" the matrix of covariances between our seven individual management quality proxies using the minimum number of factors. In contrast, the aim of principal component analysis is to break down the above covariance matrix into a set of orthogonal components equal to the number of the individual proxies. Given that our objective here is to identify a factor that embodies the underlying unobservable construct, namely, "management quality", we believe that the former method is more appropriate here.

[15]In a robustness check that we describe later, we address the possibility that our results are driven by the presence of *Team Size* in the management quality factor, and not the other quality measures. To address this concern, we recalculate the management quality factor by excluding *Team Size* from the common factor analysis. We show that our results are similar when we use the first factor derived from this alternative model.

Patent data are subject to two types of truncation problems. First, patents are recorded in the data set only after they are granted and the lag between patent applications and patent grants is significant (about two years on average). As we approach the last few years for which there are patent data available, we observe a smaller number of patent applications that are eventually granted. Many patent applications filed during these years were still under review and had not been granted by 2011. We partially mitigate this bias by restricting our analyses to two years before the patent data ends (i.e., in 2009). Further, following Hall, Jaffe, and Trajtenberg (2001), we correct this bias by dividing each patent for each firm-year by the mean number of patents for all firms for that year in the same 3-digit technology class as the patent. The second type of truncation problem is stemming from citation counts. Patents tend to receive citations over a long period of time, so the citation counts of more recent patents are significantly downward biased. Following Hall, Jaffe, and Trajtenberg (2001), this bias is accounted for by scaling citations of a given patent by the total number of citations received by all patents in that year in the same 3-digit technology class as the patent. Note that the above methodology gives us class-adjusted measures of patents and citations, which adjust for trends in innovative activity in particular industries.

We construct three measures for a firm's annual innovative output based on the patent application year.[16] The first measure, *Ln(Patents)*, is the natural logarithm of one plus the class-adjusted patent count for a firm in a given year. Specifically, this variable counts the total number of (class-adjusted) patent applications filed that year that were eventually granted. However, a simple count of patents may not distinguish breakthrough innovations from incremental technological discoveries. Therefore, we consider two additional measures. The second measure, *Ln(Citations)*, is the natural logarithm of one plus the class-adjusted total number of citations received by the firm's patents filed in a given year. The third measure, *Ln(Citations/Patent)*, is constructed by taking natural logarithm of one plus the total number of class-adjusted citations a firms receives on all the patents it applies for in a given year and normalizing it by one plus the total number of class-adjusted patents applied for in that year. We take the natural logarithm because the distribution of patents and citations are right skewed. To avoid losing observations with zero patents or zero citations, we add one to the actual values. Table 1 also reports the summary statistics of our innovation

[16]As suggested in the innovation literature (e.g., Griliches, Pakes, and Hall (1988)), the application year is more important than the grant year since it is closer to the time of the actual innovation.

measures. The median R&D to assets ($R\&D/Assets$) ratio in our sample is 1 percent. Further, an median (average) firm in our sample has 0.860 (0) class-adjusted patents. The median (average) firm in our sample has 0.034 (0) class-adjusted citations.

3.4 Measures of Inventor Mobility

To identify the inventor mobility, we collect inventor information of each patent from the U.S Patent Inventor Database (1975-2010) (see Lai, D'Amour, Yu, Sun, and Fleming (2013)). The U.S. Patent Inventor Database includes inventor names, inventor addresses, assignee names, application and grant date for each patent. More importantly, it identifies unique inventors over time so that we could possibly track the moves of each inventor. Following Marx, Strumsky, and Fleming (2009), we identify mobile inventors as changing employers if he has ever filed two successive patent applications that are assigned to different firms (or organizations). As we need at least two patents to detect a move, inventors that have filed a single patent throughout their career are necessarily excluded from our analysis.

We assume the inventor's move to occur in the year when he filed his first patent in a given firm. For a given firm, an inventor's move-in year is the year when he filed his first patent in this firm; the inventor's move-out year is that when he filed his first patent in the subsequent firm. For the inventor's very last employer, we assume that the inventor stayed with that firm and did not move out.[17] For example, the inventor named Christopher L. Holderness has filed two patent applications till 2010. He filed patent application with Corning Inc. in 1999 and then with Dell Inc. in 2003. In accordance with our assumption, for Corning, Mr. Holderness's move-in year is 1999 and move-out year is 2003; and for Dell, Mr. Holderness's move-in year is 2003, and he has stayed with Dell since 2003. Once we identify each mobile inventor's move-in and move-out year, we aggregate the number of mobile inventors that move in and move out at the firm-year level to obtain the total inflows and outflows of mobile inventors for a given firm in a year. We define the difference between the natural logarithm of one plus the inflow and the natural logarithm of one plus the outflow as the net inflow of mobile inventors ($Net\ Inflow_t$). For firms without any mobile inventors, we assign zero values to the net inflow of mobile inventors.

[17] As a robustness check, we redefine the dates that the inventor moved out of his last employer as one or two years after he filed his last patent in that firm. Our results remain qualitatively similar with this alternative definition.

To examine the moves of inventors with different innovative ability, we classify the mobile inventors into two groups, namely, high-quality and low-quality inventors. For each inventor, we look at the average quality of his historical patents, i.e., the citations per patent for all the patents he filed prior to the current year. If an inventor's historical citations per patent is higher than the sample median, he is considered as a high-quality inventor; otherwise, he is a low-quality inventors. We aggregate the mobility measures of high-quality (low-quality) inventors at the firm-year level to get the annual inflow and outflow of the high-quality (low-quality) inventors for a firm.

We use the quality of incoming (outgoing) inventors as in a given year as another measure of the quality of inventors joining (leaving) a firm. Specifically, the measure of average quality of incoming inventors for firm i in year t, $Incoming\ Quality_{i,t}$, is the natural logarithm of one plus the average historical citations per patent of all inventors that move into the firm in year t. The measure for average quality of outgoing inventors for firm i in year t, $Outgoing\ Quality_{i,t}$, is the natural logarithm of one plus the average historical citations per patent of all inventors that move out. $Net\ Quality\ Change_{i,t}$ is defined as the difference between $Incoming\ Quality_{i,t}$ and $Outgoing\ Quality_{i,t}$, which captures the change in inventor quality at the firm-year level.

3.5 Other Variables

Following the innovation literature, we obtain firms' financial information from Compustat and price data from CRSP and control for a number of firm characteristics that could affect firms' innovation output. We compute all variables for firm i over its fiscal year t. The controls include *Ln(Assets)*, which is the natural logarithm of book value of total assets; *M/B,* which is the Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA*, which is defined as operating income before depreciation divided by total assets; *CAPEX/Assets*, which is defined as capital expenditures over total assets; *Stock Return*, which is the firm's prior 12 months annual compounded stock return; and *Average Tenure*. To minimize the effect of outliers, we winsorize all independent variables at the 1st and 99th percentiles. Table 1 provides summary statistics for the control variables described above. Median firm size in our sample is $323 million, suggesting that our sample consists of mainly mid-size and large firms. The median firm in our sample has an ROA of 10.2%, CAPEX-to-assets ratio of 3.5%, Tobin's Q of 1.6, and annual stock return of 3.3%.

4 Empirical Tests and Results

4.1 Methodology and Identification

We empirically test whether there is a link between management quality and corporate innovation. Therefore, for our baseline analyses we conduct OLS regressions of our innovation measures on our management quality measures described above. However, the management quality of a firm may be endogenously related to corporate innovation. For instance, higher quality managers may choose to work for higher quality firms. In other words, there may be an endogenous matching between management quality and firm quality. In order to address the above endogeneity concern, we use an instrumental variable (IV) analysis. In our IV analysis, we exploit the strong correlation between the movement of executives across firms and the number of acquisitions in the industry the firm belongs to. In other words, we instrument for top management quality (as measured by our management quality factor) using a plausibly exogenous shock to the supply of top executives available for hire by a firm, namely, the number of acquisitions in the firm's industry four and five years prior. In doing the above, we broadly follow the methodology of Ewens and Marx (2014), who use a similar instrument in their analysis of the relation between value creation by venture capitalists and executive replacements. Similar to Ewens and Marx (2014), we are motivated to use the above instrument by the fact that potential managers available for hire by a firm often come from established firms in the same industry and may leave such firms as a result of acquisitions.

We collect information on mergers and acquisitions from the SDC Mergers & Acquisitions Database and construct the above instrument by counting the number of acquisitions of public targets made by established firms in the sample firm's industry (identified by two-digit SIC codes) four and five years prior. The four to five-year lag that we use stems from the popular retention contracts employed by the acquirers for target firms. These contracts often compensate the managers of target firms for lost compensation for two to four years and provide strong incentives for these managers to stay with the target firms for another few years. The expiration of these contracts provides a source of exogenous variation to the supply of managers available for hire by a firm and therefore to the quality of a firm's management team.

We first conduct a preliminary analysis of the relation between past acquisition activity in a firm's industry and the management quality of a firm (as measured by *MQF*) by running the following regression:

$$MQF_{i,t} = \alpha + \sum_{j=0}^{5} \beta_j Acquisitions(t-j) + \gamma Z_{i,t} + Industry\ dummies + Year\ dummies \quad (2)$$

where *Acquisitions(t-j)* is the number of publicly traded targets acquired by publicly traded firms in the sample firm's industry in the jth year prior to the current year t (when the management quality is measured), and j=0, 1, 2, 3, 4, 5; and Z is a set of control variables.

Our estimates of β_j from regression (2) reveal that there is a reduced form correlation between acquisitions in the same industry as the firm and the firm's top management quality (*MQF*). We find that only the coefficients three years to five years prior (*Acquisitions(t-3)*, *Acquisitions(t-4)*, and *Acquisitions(t-5)*) are positive: the coefficients of *Acquisitions(t-4)* and *Acquisitions(t-5)* are statistically significant at the one percent level, while that of *Acquisitions(t-3)* is statistically insignificant. The above pattern presents relatively strong evidence for the above proposed relation between acquisitions in a firm's industry and the top management quality of the firm.

To instrument for the the top management of firm i at time t, we therefore run the first-stage regression of our 2SLS analysis as follows:[18]

$$MQF_{i,t} = \alpha + \beta_4 Acquisitions(t-4) + \beta_5 Acquisitions(t-5) + \gamma Z_{i,t} + Industry\ dummies + Year\ dummies \quad (3)$$

In each of our IV regressions, we include the Herfindahl-Hirschman Index in the firm's industry to control for time-varying industry competition, ensuring that our instrument will not affect innovation through channels other than the predicted management quality. Given the above specification, and the fact that the number of acquisitions in a firm's industry in the past four and five years is unlikely to be related to the firm's quality, the exclusion restriction for our instrument is likely to be satisfied. Column 1 of Table 6 (Panel A) reports the results of the first stage of our IV analysis. The coefficients of *Acquisitions(t-4)* and *Acquisitions(t-5)* have the predicted sign and are statistically significant. The first-stage F-statistic is 10.52 which is significant at one percent level. This indi-

[18] Since the coefficient on $Acquisitions(t-3)$ is insignificant, we will use $Acquisitions(t-4)$ and $Acquisitions(t-5)$ as our instruments.

cates that *Acquisitions(t-4)* and *Acquisitions(t-5)* are relevant instruments for management quality. We use these two instruments for all our IV analyses on the relation between management quality and innovation, as well as for our analyses of the mechanisms through which management quality affects innovation. We will report the second-stage results of these IV analyses in the individual subsections after we first present our baseline (OLS regression) analyses.

4.2 The Effect of Management Quality on R&D Expenditures

We expect that firms with higher quality management teams are likely to devote a greater amount of resources to innovative activities, i.e., management quality is positively associated with innovation input. In this section, we empirically test this hypothesis (**H1**) by estimating the following regression:

$$R\&D/Assets_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ dummies + Year\ dummies + \epsilon_{i,t} \qquad (4)$$

where i indexes firm and t indexes time and n equals one, two or three. The management quality measure, *MQF* is measured for firm i over its fiscal year t. Z is a vector of control variables that could affect a firm's innovation output, which includes *Ln(Assets)*, *M/B*, *ROA*, *CAPEX/Assets*, *Stock Return*, and *Average Tenure*. We include year dummies and 2-digit SIC industry dummies.[19,20] In all regressions throughout the paper, standard errors are clustered at the firm level.

Table 3 reports the regression estimation results for equation (4). Columns (1)-(3) correspond to R&D to assets ratios of one, two and three years ahead of the year in which management quality (i.e., *MQF*) is measured. The coefficients of *MQF* in all three specifications are positive and both statistically and economically significant. For example, the coefficient in Column (1) suggests that a one inter-quartile increase in *MQF* is associated with an increase of 0.74 percentage point in *R&D/Assets* for next year, which is equivalent to 70% of the sample median. These results suggest that a firm's innovation input, as measured by R&D expenditures, is positively associated with its management quality, consistent with hypothesis (**H1**).

[19] Our results are insensitive to defining industry dummies at 3-digit or 4-digit SIC code level.

[20] For robustness, we also examine the same regressions controlling for industry, year and state fixed effects, industry×year fixed effects, and industry×state×year fixed effects. We report results controlling for industry×state×year fixed effects in Table A3 in the Internet Appendix. We find that the results remain qualitatively similar to those reported here.

4.3 The Effect of Management Quality on Corporate Innovation

In this section, we test the relationship between management quality and corporate innovation output, both in terms of quantity (as measured by the number of patents), and quality (as measured by citations and citations per patent), which corresponds to our second hypothesis (**H2**). We estimate the following models:

$$Ln(Patents)_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ dummies + Year\ dummies + \epsilon_{i,t} \quad (5)$$

$$Ln(Citations)_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ dummies + Year\ dummies + \epsilon_{i,t} \quad (6)$$

$$Ln(Citations/Patent)_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + Industry\ dummies + Year\ dummies + \epsilon_{i,t} \quad (7)$$

where i indexes firm and t indexes time and n equals one, two or three. Since the innovation process takes time, we examine the effect of a firm's management quality on its innovation as of one, two, and three years after the year in which *MQF* is measured; as well as the cumulative innovation output within these three years. Z is the set of control variables similar to those in the previous section, but now also includes *R&D/Assets.*

Panels A, B and C of Table 4 report the OLS estimation results for equations (5), (6) and (7), respectively. Across all specifications, the coefficients on *MQF* are positive and significant, both statistically and economically. For example, Column (1) in Panel A of Table 4 suggests that a one inter-quartile range increase in *MQF* is associated with an increase of 0.116 in *Ln(Patents)*. This is economically large and corresponds to a 12.3% increase in the next year's number of patents. The impact of *MQF* is even larger on the cumulative patenting activity over the next three years. With regard to control variables, firms that are larger and those with higher Tobin's Q, higher R&D expenditures, and worse stock performance are associated with more innovation output.[21]

Table 5 reports the results for regressions where we regress the three innovation output measures on each individual management quality measure.[22] Specifically, we use the values of *Team Size*, *MBA*, *Prior Work Experience*, *Education Connections*, *Employment Connections*, *Prior Board*

[21] In a robustness check we describe later, we conduct these regressions using the sample of firms that have filed at least one patent application throughout our sample period of 1999-2009. Our results (see Table A1 in the Internet Appendix) are qualitatively similar to those reported here.

[22] Note that the coefficients and standard errors in Panel C of Table 5 are multiplied by 100 for ease of reading.

Experience and *PhD* as independent variables in Columns (1) through (7) across all panels in Table 5.[23] Except for *Prior Work Experience* and *Prior Board Experience*, we find positive and significant effects of each individual management quality measure on all three innovation output measures. These effects are economically significant as well. For instance, a one inter-quartile range increase in *MBA* corresponds to a 4% increase in patenting activity. These findings in this section support our hypothesis (**H2**), that is, management quality has a positive impact on the quantity and quality of the firm's innovation output.

We now turn to our IV analysis of the relation between top management quality and innovation output. Columns (2)-(5) of Panel A in Table 6 report the second-stage results of our 2SLS regressions using one, two, and three year ahead patent counts and cumulative patent counts over the next three years as our dependent variables. Panel B and Panel C correspond to second-stage results using the total number of citations and the number of citations per patent as dependent variables, respectively. We find that, after controlling for the potential endogeneity between *MQF* and innovation output using our IV analysis, our management quality factor still has a significantly positive impact on firms' patent counts, total number of citations, and citations per patent in all specifications, except the three-year cumulative citations per patent. The coefficients on *MQF* are consistent and larger than those reported in the OLS analyses above. Broadly, our results suggest that management quality is positively and causally related to firms' innovation output.

4.4 The Effect of Management Quality on Innovative Efficiency

Having established that firms with higher quality management teams are characterized by greater innovation input as well as greater innovation output and higher quality innovation output, we test whether such firms are able to use R&D resources more efficiently in producing innovation output. This corresponds to our third hypothesis (**H3**). We construct two measures for innovative efficiency for the empirical test. Following Hirshleifer, Hsu, and Li (2013), innovative efficiency here refers to the ability of the firm to generate patents and citations per dollar of R&D expenditures. The two measures for innovative efficiency, *Patents/R&D* (*Citations/R&D*) are the natural logarithm of one plus the ratio of truncation-adjusted patent counts (truncation-adjusted number of citations) scaled by firm's R&D capital in the past five years. Following Chan, Lakonishok, and Sougiannis

[23] Our results are qualitatively similar when we use size-adjusted individual management quality measures.

(2001) and Lev, Sarath, and Sougiannis (2005), we define a firm's R&D capital as cumulative R&D expenses assuming an annual depreciation rate of 20%. Specifically, they are defined by the following formula:

$$Patents/R\&D_{i,t} = Ln(1 + \frac{Patents_{i,t}}{R\&D_{i,t} + 0.8R\&D_{i,t-1} + 0.6R\&D_{i,t-2} + 0.4R\&D_{i,t-3} + 0.2R\&D_{i,t-4}}) \tag{8}$$

$$Citations/R\&D_{i,t} = Ln(1 + \frac{Citations_{i,t}}{R\&D_{i,t} + 0.8R\&D_{i,t-1} + 0.6R\&D_{i,t-2} + 0.4R\&D_{i,t-3} + 0.2R\&D_{i,t-4}}) \tag{9}$$

where $Patents_{i,t}$ and $Citations_{i,t}$ denote the truncation-adjusted number of patents that firm i filed in year t and the number of citations received by those patents; $R\&D_{i,t}$ denotes firm i's R&D expenses in fiscal year t.

Table 7 reports the OLS regression results for the effect of management quality on innovative efficiency.[24] Columns (1), (2), and (3) correspond to regressions using $Patents/R\&D$ one, two and three years from now as dependent variables, respectively. Columns (4), (5), and (6) correspond to regressions using $Citations/R\&D$ one, two, and three years from now as dependent variables, respectively. We find the coefficients on management quality factor are positive and significant across all specifications. We also conduct IV analyses for innovative efficiency using the same instrument variables as described in earlier sections.[25] In untabulated results, we find that the coefficients of MQF for these regressions remain positive and statistically significant. Collectively, our evidence indicates that firms with higher management quality are better at getting more "bang for the buck", i.e, use R&D resources more efficiently in generating higher innovation output.

4.5 The Effect of Management Quality on Corporate Innovation: Interaction Tests

In this section, we dig deeper into whether the relation between management quality and innovation productivity is stronger in some industries than in others. We thus conduct interaction tests based

[24]This table does not have *R&D/Assets* as a control since the dependent variable is already normalizedby R&D expenditures. In unreported tests, we control these regressions for *R&D/Assets* and find qualitatively similar results. Results available from authors upon request.

[25]The IV regression results for innovative efficiency are not reported in order to save space. These results are available from authors upon request.

on the hypotheses (**H4)** and (**H5**), which predict that management team quality will have a stronger effect for firms in financially constrained industries and for firms in more competitive industries, respectively. In order to test the above hypotheses, we first interact *MQF* in our regressions with *Constrained*, a dummy variable that is equal to one if the firm operates in an industry for which the median value of external financial dependence (as calculated in Rajan and Zingales (1998)) is positive and zero otherwise. Also we interact *MQF* with *HHI*, which is the value of Herfindahl-Hirschman Index in the firm's industry (defined at the 2-digit SIC code level) in each year.

Table 8 reports the results for the interaction tests with one year ahead innovation measures as dependent variables. Columns (1), (2), and (3) report the regression results for the interaction of *MQF* and *Constrained* as well as *Constrained* as additional independent variables. The coefficient estimates on *MQF* are significantly positive for all three measures of innovation output, consistent with our previous results. More importantly, the coefficients on the interaction term ($MQF \times Constrained$) are also significantly positive for *Ln(Patents)* and *Ln(Citations)* at one percent level. This evidence indicates that firms with higher quality management are able to select better projects, use resources more efficiently, and generate greater innovation output in adverse financing environments.

We report results of the interaction tests for *MQF* and *HHI* in Columns (4), (5), and (6) in Table 8. As before, the coefficient estimates on *MQF* are significantly positive for all three innovation measures. Further, the coefficients on the interaction term ($MQF \times HHI$) are negative and significant, indicating that the positive impact of management quality on innovation becomes more pronounced as industry competition increases. Thus, the results in this section are consistent with our hypotheses (**H4**) and (**H5**).

5 Possible Mechanisms: Inventor Mobility

Our evidence is so far consistent with that management quality has positive impacts on corporate innovation. In this section, we discuss the possible underlying mechanisms through which this occurs. As argued before, higher quality management teams may provide more R&D resources, manage R&D resources better, and provide a more risk-tolerant climate for inventors to succeed in. This, in turn, may make firms with higher management quality more attractive to higher quality inventors. Thus, one way that higher quality management teams may enhance innovation is by hiring more and higher quality inventors to work for the firm. We test these conjectures below.

5.1 Management Quality and Net Inflow of Inventors

To assess the relation between management quality and the net inflow of inventors that move into the firm at the firm-year level, which corresponds to our hypothesis (**H6)**, we test the following model:

$$\textit{Net Inflow}_{i,t+n} = \alpha + \beta_1 MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} + \textit{State dummies} + \epsilon_{i,t} \tag{10}$$

where i indexes firm and t indexes time and n equals one, two or three. Z is a vector of control variables used in prior tests. As before, we include year dummies and 2-digit SIC industry dummies. Moreover, since location may impact inventors' decisions of moving into or out of a firm, we include state dummies for the state of the firm's headquarter in all regressions in this section.

Table 9 reports results for the above model. We first present the OLS regression results in Columns (1)-(3). Across all specifications, our coefficients of interest on *MQF* are significantly positive. For instance, Column (1) of Table 9 suggests that a one inter-quartile range increase in *MQF* is associated with 0.05 increase in *Net Inflow*. The economic magnitude of the effect is large given that the sample mean of *Net Inflow* is 0.21.

We then present in Columns (4)-(6) the IV regression results using the same instrumental variables as we describe in prior sections. We continue to find significant, positive and stronger effects of our management quality factor on the net inflows of inventors after controlling for the potential endogenous matching between firm quality and inventor mobility. These findings support our hypothesis (**H6),** and suggest that one mechanism through which higher quality management teams enhance firm innovation is by attracting more inventors to work for the firm.

5.2 Management Quality and High-and Low-quality Inventors

In this section, we move on to test whether higher quality managers are better at attracting higher quality inventors. Specifically, we test the following models:

$$\begin{aligned} \textit{Net Inflow of High}_{i,t+n} =& \alpha_H + \beta_H MQF_{i,t} + \gamma_H Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} \\ & + \textit{State dummies} + \epsilon_{i,t} \qquad (11) \\ \textit{Net Inflow of Low}_{i,t+n} =& \alpha_L + \beta_L MQF_{i,t} + \gamma_L Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} \\ & + \textit{State dummies} + \epsilon_{i,t} \qquad (12) \end{aligned}$$

where i indexes firm and t indexes time and n equals one, two or three. The same vector of control variables and same set of dummy variables are included as in the prior section. We statistically test whether the coefficient on *MQF* in the regression (11) is positive and significantly larger than that in regression (12), i.e., $\beta_H > 0$ and $\beta_H > \beta_L$.

Panel A of Table 10 reports the regression estimation results using $\textit{Net Inflow of High}_{i,t}$ and $\textit{Net Inflow of Low}_{i,t}$ as dependent variables calculated at one, two, and three years subsequent to the current year. We find that the coefficients on *MQF* are positive using both dependent variables, indicating that management quality has positive impacts on the net inflow of both high-quality and low-quality inventors. More importantly, the effect of *MQF* on the net inflow of high-quality inventors is economically 10 times larger than on the net inflow of low-quality inventors across all time horizons. We test the statistical significance of the difference for the coefficients on *MQF* for high quality versus low quality inventors and report the test results in Panel B of Table 10. All the differences are statistically significant at 1% level. To confirm the above relations are causal, we instrument for *MQF* using the industry acquisitions four to five years prior as described in earlier sections. In untabulated results, we find consistent and stronger results compared to those reported in Table 10.[26] Collectively, these findings provide further evidence that higher quality managers are indeed able to hire a greater number of high-quality inventors than low-quality inventors, consistent with hypothesis (**H7**).

[26]These results are not reported in order to save space and are available from the authors upon request.

5.3 Management Quality and Average Inventor Quality

We further investigate whether management quality is positively associated with the average incoming inventor quality for a firm. As before, the quality for each inventor is measured as the citations per patent for the patents he has filed prior to the current year. To understand the effect of management quality on a firm's average inventor quality, we consider the following three models:

$$\begin{aligned} \textit{Incoming Quality}_{i,t+n} =& \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} \\ &+ \textit{State dummies} + \epsilon_{i,t} \qquad (13) \\ \textit{Outgoing Quality}_{i,t+n} =& \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} \\ &+ \textit{State dummies} + \epsilon_{i,t} \qquad (14) \\ \textit{Net Quality Change}_{i,t+n} =& \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} \\ &+ \textit{State dummies} + \epsilon_{i,t} \qquad (15) \end{aligned}$$

Recall that $\textit{Net Quality Change}_{i,t}$ is defined as the difference between $\textit{Incoming Quality}_{i,t}$ and $\textit{Outgoing Quality}_{i,t}$, which captures the net change in average inventor quality of the firm's inventor team in a given year.

Panels A and B of Table 11 reports the OLS and IV regression results for the above models, using the above three dependent variables measured over the subsequent one, two and three years, respectively.[27] Across all time horizons, we find that the coefficients on *MQF* for $\textit{Incoming Quality}_{i,t}$ and $\textit{Outgoing Quality}_{i,t}$ are both significantly positive. This suggests that, for higher management quality firms, the newly-hired inventors as well as laid-off inventors are more innovative compared with those for lower management quality firms.

In each panel, Columns (1), (4) and (7) report the effect of management quality on the net change of average inventor quality for a firm (i.e., *Net Quality Change*). The coefficients on *MQF* are both positive and significant at the one percent level. The economic magnitude of the impact is significant as well. For instance, Column (1) of Panel A suggests that a one inter-quartile range increase in *MQF* leads to a 13% net increase in the next year's average inventor quality. Columns (2), (5), and (8) report the regressions with *Incoming Quality* as the dependent variable over the

[27] Note that coefficients and standard errors in Table 11 are multiplied by 100 for ease of readability.

subsequent one, two, and three years, respectively. Similarly, Columns (3), (6), and (9) report the regressions with *Outgoing Quality* as the dependent variable over the subsequent one, two, and three years, respectively. Consistent with the results for *Net Quality Change*, while higher quality management firms gain as well as lose higher quality inventors, the gains are larger than the losses. The IV regression results in Panel B suggest that the effects of management quality factor on the quality of inventors become even stronger after taking into account the potential endogeneity concerns. Our results provide causal evidence that higher management quality is associated with greater increase in average inventor quality of a firm, again consistent with hypothesis (**H7**).

5.4 Management Quality and Corporate Innovation Strategies

In this section, we further investigate the possible differences in the innovation strategies adopted by firms with higher versus lower management quality. As we have conjectured earlier, if firms with higher quality management teams engage in more explorative innovative strategies, such firms should have a greater number of patents in the two tails of the patent quality distribution,.i.e., very successful and very unsuccessful patents. On the other hand, if firms with higher quality management teams adopt more exploitative strategies, such firms will have more moderately successful patents. To understand firms' innovative strategies, we categorize the sample pool of patents applied between 1999 and 2009 in to three groups: (i) *Top 10%*, defined as patents receiving the number of citations in the top 10% among all patents in the same 3-digit technology class and application year; (ii) *No Cites*, defined as those receiving zero citations till 2009; and (iii) *Moderate Cites*, defined as those receiving at least one citation but not in the top 10%. Balsmeier, Fleming, and Manso (2014) follow a similar approach in their study of the relation between the independence of firms' corporate boards and their innovation strategies. Using the number of patents in each category, we estimate the following models:

$$\textit{Top 10\%}_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} + \epsilon_{i,t} \quad (16)$$

$$\textit{No Cites}_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} + \epsilon_{i,t} \quad (17)$$

$$\textit{Moderate Cites}_{i,t+n} = \alpha + \beta MQF_{i,t} + \gamma Z_{i,t} + \textit{Industry dummies} + \textit{Year dummies} + \epsilon_{i,t} \quad (18)$$

Table 12 reports the estimation results for the above equations. Columns (1), (2), and (3) across all panels of Table 12 correspond to regression results using the natural logarithm of one plus the number of patents in the aforementioned three groups as dependent variables (*Top 10%*, *No Cites* and *Moderate Cites*, respectively). Panels A, B, and C correspond to regression results using one, two and three year ahead dependent variables, respectively. The same set of control variables used in Table 4 are included in all specifications and coefficient estimates on the controls are not reported in order to save space (available from authors upon request). Columns (4), (5), and (6) report the tests of statistical difference between coefficient estimates across the regression models in Columns (1), (2), and (3). In all specifications in Table 12, we find the coefficients on *MQF* are positive and statistically and economically significant. These results indicate that firms with higher quality management teams engage in both explorative and exploitative innovative strategies. Such firms are able to produce more patents in all three categories. More interestingly, the coefficients in Column (1) are much bigger than those in Column (2) or (3), and Columns (4) and (5) confirm that these differences are statistically significant. These findings suggest that management quality has a more pronounced effect on successful patents than unsuccessful patents or average patents. Higher management quality firms are better at motivating successful patents that are highly cited afterwards. Further, management quality seems to have no differential impact on unsuccessful patents and average patents. Broadly, the results in this section support both hypotheses (**H8A**) and (**H8B**).

6 Robustness Tests

6.1 Sample of Innovative Firms

We use the entire BoardEx-KPSS patent-Compustat-CRSP merged sample in our main analysis and assign zero patents to those firms without any patent record following prior studies (see, e.g., Fang, Tian, and Tice (2014) and Seru (2014)). One concern of measurement error may be that some firms in our sample may not involve in any innovative activities throughout their development process (i.e., such firms may not appear as a patent assignee in the patent dataset). Thus, we re-estimate our base case regressions using a sample consisting of innovative firms only, which refer to firms that have filed at least one patent application over our sample period of 1999-2009. We therefore alleviate the measurement error concern by studying a more accurate but smaller sample. The results are reported in Table A1 of our Internet Appendix (not to be published).[28] The positive relation between our management quality factor and all three measures of innovation output continue to hold in this sample.

6.2 Alternative Management Quality Factor

In this section, we re-run our common factor analysis using all proxies other than management team size. We do this to ensure that our results are not driven by any team size-specific effects. Thus, we re-estimate the management quality factor after excluding team size and re-run the regressions between this alternative management quality factor and corporate innovation.

The results of these tests are reported in Table A2 of our Internet Appendix. Panels A, B and C report the OLS regression results using the number of patents, total number of citations and citations per patent as dependent variables, respectively. We find that, consistent with our previous results, all three measures of innovation output are positively related to this alternative management quality factor.

7 Conclusion

We analyze the effect of the human capital or "quality" of the top management of a firm on its innovation activities. We extract a "management quality factor" using common factor analysis on various individual proxies for the quality of a firm's management team, such as management team size, fraction of managers with MBAs, the average employment- and education-based connections of each manager in the management team, fraction of members with prior work experience in a top management position, the average number of prior board positions that each manager serves on, and the fraction of managers with doctoral degrees. Firms with higher quality management teams not only invest more in innovation (as measured by R&D expenditures), but also have a greater quantity and quality of innovation, as measured by the number of patents and citations per patent, respectively. We control for the endogenous matching of higher quality managers and higher quality firms using an IV analysis where we use a plausibly exogenous shock to the supply of new managers available for hire by a firm (which, in turn, will affect of the quality of a firm's top

[28] While we use our full set of control variables in our regressions in Tables A1, A2, and A3, we do not show the coefficient estimates for these controls to conserve space.

management team) as an instrument for top management human capital. An important channel through which higher management quality firms achieve greater innovation success is by hiring a larger number of inventors (controlling for R&D expenditures), and also by hiring higher quality inventors (as measured by their prior citations per patent record). Finally, we show that higher quality management team firms seem to pursue both exploratory and exploitative innovations.

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Table 1: Summary Statistics

This table reports summary statistics for our sample of public firms between 1999 and 2009. *Adjusted Patents* is the truncation-adjusted number of patents that a firm filed in a given year; *Adjusted Citations* is the total adjusted number of citations received by the firm's patents filed in a year; *Adjusted Citations/Patent* is the adjusted number of citations per patent for a firm in a given year. *Team Size* is the number of managers (VP or higher) in a firm's management team; *MBA* is the fraction of the managers that have MBA degrees; *Prior Work Experience* is the fraction of top managers that have experience working as VP or higher in other companies; *Education Connections* is the average number of graduate connections that each manager has through education (if two managers graduated from the same university with the same degree within one year of each other, those two are defined as connected); *Employment Connections* is the average number of connections that each manager has through prior employment (if two managers worked in the same previous company during overlapping time periods, either as managers or directors, those two are defined as connected); *Prior Board Experience* is the average number of board positions that each manager has served on; *PhD* is the fraction of the managers that have PhD degrees; *Total Assets* is the firm's total assets; *ROA* is defined as operating income before depreciation divided by total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm.

Variable	Obs	Mean	Std.Dev.	Min	1st Quartile	Median	3rd Quartile	Max
Adjusted Patents	30432	0.862	2.308	0.000	0.000	0.000	0.309	10.439
Adjusted Citations	30432	0.034	0.108	0.000	0.000	0.000	0.000	0.495
Adjusted Citations/Patent	30432	0.002	0.006	0.000	0.000	0.000	0.000	0.025
Team Size	30432	7.751	4.469	2.000	5.000	7.000	10.000	30.000
MBA	30432	0.230	0.195	0.000	0.000	0.200	0.333	1.000
Prior Work Experience	30432	0.141	0.172	0.000	0.000	0.100	0.235	1.000
Education Connections	30432	1.417	3.296	0.000	0.000	0.000	1.200	55.500
Employment Connections	30432	17.949	11.108	1.000	10.000	15.400	23.000	98.667
Prior Board Experience	30432	0.071	0.149	0.000	0.000	0.000	0.100	2.667
PhD	30432	0.074	0.146	0.000	0.000	0.000	0.100	1.000
Total Assets (Million)	30432	2887.979	12991.060	0.306	83.810	322.609	1335.178	304594.000
ROA	30432	0.035	0.279	-2.041	0.014	0.102	0.163	0.424
M/B	30432	2.307	2.904	0.166	1.169	1.606	2.499	137.183
CAPEX/Assets	30432	0.065	0.088	0.000	0.017	0.035	0.074	0.542
R&D/Assets	30432	0.077	0.153	0.000	0.000	0.010	0.092	0.995
Stock Return	30432	0.173	0.767	-0.884	-0.289	0.033	0.404	3.458
Average Tenure	30432	5.833	3.319	1.000	3.571	5.200	7.333	36.500

Table 2: Common Factor Analysis

This table reports statistics related to common factor analysis. *Factor 1- Factor 7* are the common factors obtained by using common factor analysis on the firm size- and industry-adjusted *Team Size, MBA, Prior Work Experience, Education Connections, Employment Connections, Prior Board Experience,* and *PhD*. *Team Size* is the number of managers (VP or higher) in a firm's management team; *MBA* is the fraction of the managers that have MBA degrees; *Prior Work Experience* is the fraction of top managers that have experience working as VP or higher in other companies; *Education Connections* is the average number of graduate connections that each manager has through education (if two managers graduate from the same university with the same degree within one year of each other, those two are defined as connected); *Employment Connections* is the average number of connections that each manager has through prior employment (if two managers worked in the same previous company during overlapping time periods, either as managers or directors, those two are defined as connected); *Prior Board Experience* is the average number of board positions that each manager has served on; *PhD* is the fraction of the managers that have PhD degrees. Panel A reports the eigenvalues for the seven factors to mimic the correlation matrix of the original variables. Panel B reports the communality of the original variables and the correlation and loadings on the first factor. Panel C reports the descriptive statistics of the first factor.

Panel A: Eigenvalues

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
1.172	0.577	0.216	0.042	-0.022	-0.195	-0.301

Panel B: Summary For Factor Analysis

Variable	Loadings On First Factor	Correlation with First Factor	Communality
Team Size	0.513	0.841	0.264
MBA	0.141	0.078	0.020
Prior Work Experience	0.368	0.233	0.135
Education Connections	0.149	0.086	0.022
Employment Connections	0.803	0.906	0.645
Prior Board Experience	0.288	0.094	0.083
PhD	0.053	0.038	0.003

Panel C: Summary Statistics of First Factor

Obs	Mean	Std.Dev.	Min	1st Quartile	Median	3rd Quartile	Max
30,432	0.013	0.758	-1.992	-0.472	-0.040	0.447	2.315

Table 3: The Effect of Management Quality on R&D Expenditures

This table reports the OLS regression results of the ratio of R&D expenditures to total assets (*R&D/Assets*) on management quality factor (*MQF*). *R&D/Assets* is defined as research and development expenses divided by total assets; *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

	(1)	(2)	(3)
Variable	$R\&D/Assets_{t+1}$	$R\&D/Assets_{t+2}$	$R\&D/Assets_{t+3}$
MQF	0.008***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)
Ln(Assets)	-0.004***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
M/B	0.057***	0.043***	0.039***
	(0.002)	(0.002)	(0.002)
ROA	-0.216***	-0.198***	-0.194***
	(0.010)	(0.010)	(0.010)
CAPEX/Assets	-0.052***	-0.052***	-0.047***
	(0.011)	(0.011)	(0.012)
Stock Return	-0.000	-0.006***	-0.004***
	(0.001)	(0.001)	(0.001)
Average Tenure	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Observations	27,688	23,741	19,887
Adjusted R-squared	0.559	0.493	0.472
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 4: The Effect of Management Quality on Quantity and Quality of Corporate Innovation

This table reports the OLS regression results of quantity and quality of corporate innovation on management quality factor (*MQF*). Panels A, B and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Three-Year Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed over the next three years; *Three-Year Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed over the next three years; *Three-Year Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent received by the firm's patents filed over the next three years. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: The Effect of MQF on the Number of Patents

	(1)	(2)	(3)	(4)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$	Three-Year Ln(Patents)
MQF	0.127***	0.129***	0.128***	0.237***
	(0.011)	(0.012)	(0.013)	(0.020)
Ln(Assets)	0.146***	0.142***	0.138***	0.247***
	(0.006)	(0.006)	(0.006)	(0.009)
M/B	0.113***	0.121***	0.122***	0.195***
	(0.011)	(0.012)	(0.012)	(0.019)
ROA	-0.010	0.002	0.005	0.008
	(0.021)	(0.022)	(0.023)	(0.040)
CAPEX/Assets	-0.042	-0.021	-0.008	-0.002
	(0.064)	(0.066)	(0.070)	(0.114)
R&D/Assets	0.235***	0.190***	0.157***	0.484***
	(0.045)	(0.045)	(0.045)	(0.077)
Stock Return	-0.031***	-0.026***	-0.016***	-0.029***
	(0.005)	(0.005)	(0.005)	(0.008)
Average Tenure	0.002	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.003)
Observations	27,688	24,519	21,250	21,250
Adjusted R-squared	0.390	0.384	0.375	0.452
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: The Effect of MQF on the Total Number of Citations				
	(1)	(2)	(3)	(4)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$	Three-Year Ln(Citations)
MQF	0.016***	0.016***	0.016***	0.051***
	(0.002)	(0.002)	(0.002)	(0.006)
Ln(Assets)	0.018***	0.017***	0.017***	0.052***
	(0.001)	(0.001)	(0.001)	(0.003)
M/B	0.013***	0.013***	0.013***	0.036***
	(0.002)	(0.002)	(0.002)	(0.005)
ROA	-0.010***	-0.010***	-0.008**	-0.026***
	(0.003)	(0.003)	(0.003)	(0.009)
CAPEX/Assets	-0.006	-0.008	-0.009	-0.007
	(0.010)	(0.010)	(0.010)	(0.030)
R&D/Assets	-0.000	-0.005	-0.005	-0.007
	(0.006)	(0.006)	(0.006)	(0.017)
Stock Return	-0.003***	-0.003***	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)
Average Tenure	0.000	0.000	0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.001)
Observations	27,688	24,519	21,250	21,250
Adjusted R-squared	0.256	0.251	0.241	0.310
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel C: The Effect of MQF on the Number of Citations per Patent				
	(1)	(2)	(3)	(4)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$	Three-Year Ln(Citations/Patent)
MQF	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Assets)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
M/B	0.000***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
CAPEX/Assets	-0.000	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
R&D/Assets	0.001**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)
Stock Return	-0.000*	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Average Tenure	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	27,688	24,519	21,250	21,250
Adjusted R-squared	0.140	0.139	0.136	0.134
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 5: The Effect of Individual Management Quality Measures on Corporate Innovation

This table reports the OLS regression results of corporate innovation on individual management quality factor variables. Panels A, B and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Team Size* is the number of managers (VP or higher) in a firm's management team; *MBA* is the fraction of the managers that have MBA degrees; *Prior Work Experience* is the fraction of top managers that have experience working as VP or higher in other companies; *Education Connections* is the average number of graduate connections that each manager has through education (if two managers graduate from the same university with the same degree within one year of each other, those two are defined as connected); *Employment Connections* is the average number of connections that each manager has through prior employment (if two managers worked in the same previous company during overlapping time periods, either as managers or directors, those two are defined as connected); *Prior Board Experience* is the average number of board positions that each manager has served on; *PhD* is the fraction of the managers that have PhD degrees. Control variables are the same as in Table 4 in all regressions and coefficient estimates on controls are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. Coefficients and standard errors in Panel C are multiplied by 100. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: The Effect of Individual Management Quality Measures on the Number of Patents

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Team Size	0.029***						
	(0.003)						
MBA		0.120***					
		(0.033)					
Prior Work Experience			0.035				
			(0.035)				
Education Connections				0.012***			
				(0.002)			
Employment Connections					0.013***		
					(0.001)		
Prior Board Experience						-0.002	
						(0.026)	
PhD							0.356***
							(0.057)
Observations	27,688	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.389	0.370	0.369	0.372	0.391	0.369	0.374
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: The Effect of Individual Management Quality Measures on the Total Number of Citations							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Team Size	0.004***						
	(0.000)						
MBA		0.013***					
		(0.005)					
Prior Work Experience			-0.006				
			(0.005)				
Education Connections				0.001***			
				(0.000)			
Employment Connections					0.002***		
					(0.000)		
Prior Board Experience						-0.002	
						(0.003)	
PhD							0.021***
							(0.007)
Observations	27,688	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.261	0.240	0.239	0.242	0.259	0.239	0.240
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: The Effect of Individual Management Quality Measures on the Number of Citations per Patent							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Team Size	0.013***						
	(0.002)						
MBA		0.059**					
		(0.027)					
Prior Work Experience			-0.004				
			(0.028)				
Education Connections				0.005***			
				(0.002)			
Employment Connections					0.005***		
					(0.001)		
Prior Board Experience						-0.024	
						(0.018)	
PhD							0.112***
							(0.042)
Observations	27,688	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.140	0.135	0.135	0.136	0.139	0.135	0.136
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: The Effect of Management Quality on Corporate Innovation: Instrumental Variable Analysis

This table reports the IV regression results of corporate innovation on management quality factor (*MQF*). The instrumental variables we use are the number of acquisitions of public targets made by established firms in the same industry (defined at 2-digit SIC code level) as the sample firm four and five years prior. Column (1) of Panel A reports the first-stage result, i.e., regressing *MQF* on the *Acquisitions(t-4) and Acquisitions(t-5)* and other controls. Columns (2)-(5) of Panel A report the second-stage results of the IV regressions using a firm's number of patents applied in a given year as dependent variables. Panels B and C report second-stage results using the total number of citations and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Three-Year Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed over the next three years; *Three-Year Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed over the next three years; *Three-Year Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent received by the firm's patents filed over the next three years. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *HHI* is the industry Herfindahl-Hirschman Index. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: First and Second-Stage Results of the Number of Patents on MQF					
	(1)	(2)	(3)	(4)	(5)
Variable	MQF	Ln(Patents)$_{t+1}$	Ln(Patents)$_{t+2}$	Ln(Patents)$_{t+3}$	Three-Year Ln(Patents)
Acquisitions(t-4)	0.001***				
	(0.000)				
Acquisitions(t-5)	0.001***				
	(0.000)				
MQF		0.878***	0.974***	0.962***	0.859***
		(0.201)	(0.203)	(0.198)	(0.202)
Ln(Assets)	0.050***	0.109***	0.103***	0.101***	0.233***
	(0.008)	(0.012)	(0.012)	(0.011)	(0.013)
M/B	0.165***	-0.011	-0.024	-0.028	0.077*
	(0.017)	(0.037)	(0.039)	(0.040)	(0.042)
ROA	-0.185***	0.125***	0.137***	0.121***	0.060
	(0.032)	(0.047)	(0.047)	(0.045)	(0.052)
CAPEX/Assets	-0.970***	0.693***	0.755***	0.683***	0.455**
	(0.096)	(0.220)	(0.214)	(0.196)	(0.213)
R&D/Assets	0.297***	0.013	-0.034	-0.029	0.388***
	(0.058)	(0.084)	(0.083)	(0.077)	(0.096)
Stock Return	-0.059***	0.013	0.027*	0.028**	-0.003
	(0.007)	(0.014)	(0.015)	(0.013)	(0.014)
Average Tenure	-0.028***	0.023***	0.026***	0.025***	0.021***
	(0.003)	(0.006)	(0.007)	(0.006)	(0.007)
HHI	-0.439	0.458	0.522	0.329	0.174
	(0.287)	(0.313)	(0.351)	(0.338)	(0.324)
Observations	27,688	27,688	24,519	21,250	21,250
Adj R-squared	0.062				
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Second-Stage Results of Total Number of Citations on MQF				
	(1)	(2)	(3)	(4)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$	Three-Year Ln(Citations)
MQF	0.106***	0.115***	0.115***	0.222***
	(0.025)	(0.025)	(0.024)	(0.048)
Ln(Assets)	0.013***	0.013***	0.012***	0.048***
	(0.002)	(0.002)	(0.001)	(0.003)
M/B	-0.002	-0.003	-0.004	0.005
	(0.005)	(0.005)	(0.005)	(0.010)
ROA	0.006	0.006	0.005	-0.006
	(0.006)	(0.006)	(0.006)	(0.013)
CAPEX/Assets	0.083***	0.083***	0.073***	0.140***
	(0.028)	(0.027)	(0.024)	(0.053)
R&D/Assets	-0.027**	-0.031***	-0.027***	-0.046**
	(0.011)	(0.010)	(0.010)	(0.023)
Stock Return	0.002	0.004**	0.003*	0.004
	(0.002)	(0.002)	(0.002)	(0.003)
Average Tenure	0.003***	0.003***	0.003***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
HHI	0.022	0.019	0.007	0.027
	(0.045)	(0.048)	(0.046)	(0.087)
Observations	27,688	24,519	21,250	21,250
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel C: Second-Stage Results of Citations per Patent on MQF				
	(1)	(2)	(3)	(4)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$	Three-Year Ln(Citations/Patent)
MQF	0.003**	0.004***	0.006***	-0.020
	(0.001)	(0.001)	(0.001)	(0.245)
Ln(Assets)	0.001***	0.000***	0.000***	0.116***
	(0.000)	(0.000)	(0.000)	(0.012)
M/B	0.000	-0.000	-0.000	0.194***
	(0.000)	(0.000)	(0.000)	(0.047)
ROA	0.000	0.000	0.001*	-0.004
	(0.000)	(0.000)	(0.000)	(0.051)
CAPEX/Assets	0.002	0.003**	0.004***	-0.155
	(0.001)	(0.001)	(0.001)	(0.228)
R&D/Assets	0.000	-0.001	-0.001	0.636***
	(0.001)	(0.001)	(0.001)	(0.092)
Stock Return	0.000	0.000	0.000*	-0.022
	(0.000)	(0.000)	(0.000)	(0.015)
Average Tenure	0.000**	0.000**	0.000***	-0.008
	(0.000)	(0.000)	(0.000)	(0.008)
HHI	-0.004*	-0.003	-0.002	0.255
	(0.002)	(0.003)	(0.003)	(0.331)
Observations	27,688	24,519	21,250	21,250
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 7: The Effect of Management Quality on Corporate Innovative Efficiency

This table reports the OLS regression results of innovative efficiency on management quality factor (*MQF*). Panel A and B report OLS and Instrumental Variable regression results, respectively. Innovative efficiency is measured by *Patents/R&D* and *Citations/R&D*. *Patents/R&D* is defined as the natural logarithm of one plus the ratio of firm's truncation-adjusted number of patents applied in a given year scaled by its R&D capital (the five-year cumulative R&D expenses assuming an annual depreciation rate of 20%); i.e., $Patents/R\&D_{i,t} = \ln(1+\frac{Patent\ count_{i,t}}{R\&D_{i,t}+0.8*R\&D_{i,t-1}+0.6*R\&D_{i,t-2}+0.4*R\&D_{i,t-3}+0.2*R\&D_{i,t-4}})$. *Citations/R&D* is defined as the natural logarithm of one plus the ratio of firm's total adjusted number of citations applied in year *t* scaled by its R&D capital (the five-year cumulative R&D expenses assuming an annual depreciation rate of 20%), i.e., $Citations/R\&D_{i,t} = \ln(1+\frac{Total\ number\ of\ citations_{i,t}}{R\&D_{i,t}+0.8*R\&D_{i,t-1}+0.6*R\&D_{i,t-2}+0.4*R\&D_{i,t-3}+0.2*R\&D_{i,t-4}})$. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Patents/R&D$_{t+1}$	Patents/R&D$_{t+2}$	Patents/R&D$_{t+3}$	Citations/R&D$_{t+1}$	Citations/R&D$_{t+2}$	Citations/R&D$_{t+3}$
MQF	0.002**	0.002***	0.002***	0.012**	0.011**	0.009**
	(0.001)	(0.001)	(0.001)	(0.006)	(0.005)	(0.005)
Ln(Assets)	-0.001**	-0.001**	-0.001	0.005*	0.004	0.003
	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)	(0.002)
M/B	0.002**	0.001	0.000	0.062***	0.042***	0.030***
	(0.001)	(0.001)	(0.001)	(0.009)	(0.008)	(0.007)
ROA	0.005***	0.005**	0.004**	0.014	0.005	0.007
	(0.002)	(0.002)	(0.002)	(0.017)	(0.017)	(0.016)
CAPEX/Assets	0.024***	0.019***	0.014**	0.324***	0.188**	0.126*
	(0.006)	(0.007)	(0.007)	(0.081)	(0.075)	(0.066)
Stock Return	-0.000	0.000	-0.000	-0.005	0.001	-0.004
	(0.001)	(0.001)	(0.000)	(0.005)	(0.005)	(0.004)
Average Tenure	0.000*	0.000	0.000*	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
Observations	15,998	14,235	12,378	15,998	14,235	12,378
Adjusted R-squared	0.117	0.118	0.111	0.233	0.208	0.182
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: The Effect of Management Quality on Corporate Innovation: Interaction Tests

This table reports the main regression results interacted with relevant variables. Columns (1)-(3) summarize regression results with *MQF* interacted with industry financial constraints, using the number of patents, the total number of citations, and the number of citations per patent for a firm in a given year as dependent variables, respectively. *Constrained* is a dummy variable, which is equal to one if the value of external finance dependence is larger than zero and zero otherwise. External finance dependence for an industry (defined at 2-digit SIC level) in a given year is defined by the method outlined in Rajan and Zingales (1998). Columns (4)-(6) summarize regression results with management quality factor (*MQF*) interacted with industry Herfindahl-Hirschman Index (*HHI*), using the number of patents, the total number of citations, and the number of citations per patent for a firm in a given year as dependent variables, respectively. *HHI* for an industry (defined at two-SIC digit level) in a given year is defined by the following formula: $\sum_{\text{i=1}}^{\text{number of firms in the same 2-digit industry}} \frac{(\text{firm sales}_{\text{i}})^2}{(\text{industry sales})^2}$. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Variable	(1) Ln(Patents)$_{t+1}$	(2) Ln(Citations)$_{t+1}$	(3) Ln(Citations/Patent)$_{t+1}$	(4) Ln(Patents)$_{t+1}$	(5) Ln(Citations)$_{t+1}$	(6) Ln(Citations/Patent)$_{t+1}$
MQF	0.105***	0.013***	0.001***	0.174***	0.021***	0.001***
	(0.012)	(0.002)	(0.000)	(0.015)	(0.002)	(0.000)
MQF × Constrained	0.077***	0.010***	-0.000			
	(0.021)	(0.003)	(0.000)			
Constrained	0.011	-0.005***	-0.000***			
	(0.011)	(0.002)	(0.000)			
MQF × HHI				-0.775***	-0.078***	-0.002*
				(0.140)	(0.022)	(0.001)
HHI				0.128	-0.019	-0.005**
				(0.179)	(0.032)	(0.002)
Ln(Assets)	0.147***	0.018***	0.001***	0.146***	0.018***	0.001***
	(0.006)	(0.001)	(0.000)	(0.006)	(0.001)	(0.000)
M/B	0.111***	0.012***	0.000***	0.111***	0.012***	0.000***
	(0.011)	(0.002)	(0.000)	(0.011)	(0.002)	(0.000)
ROA	-0.008	-0.011***	-0.000	-0.010	-0.010***	-0.000
	(0.021)	(0.003)	(0.000)	(0.021)	(0.003)	(0.000)
CAPEX/Assets	-0.035	-0.004	-0.000	-0.042	-0.006	-0.000
	(0.063)	(0.010)	(0.000)	(0.065)	(0.010)	(0.000)
R&D/Assets	0.228***	-0.001	0.001**	0.226***	-0.001	0.001**
	(0.045)	(0.006)	(0.000)	(0.045)	(0.006)	(0.000)
Stock Return	-0.031***	-0.003***	-0.000**	-0.031***	-0.003***	-0.000*
	(0.005)	(0.001)	(0.000)	(0.005)	(0.001)	(0.000)
Average Tenure	0.001	0.000	0.000	0.001	0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Observations	27,688	27,688	27,688	27,688	27,688	27,688
Adjusted R-squared	0.392	0.258	0.140	0.393	0.257	0.140
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: The Effect of Management Quality on the Mobility of Inventors

This table reports the OLS and IV regression results of the net inflow of inventors for a firm in a given year on management quality factor (*MQF*). Columns (1)-(3) report the OLS regression results; Columns (4)-(6) report the IV regression results using the same instrument variables as in Table 6, namely, the number of acquisitions of public targets made by established firms in the same industry (defined at 2-digit SIC code level) as the sample firm four and five years prior. For any inventor that filed patents in different firms or organizations, we assume a move occurred in the year when he filed the first patent in that firm. For a firm, the inventor's move-in year and move-out year are the year when the inventor filed the first patent in this firm and the year when he filed the first patent in the subsequent firm. The inflow and outflow of inventors are defined as the natural logarithm of one plus the total number of inventors that move in and that move out aggregated at the firm-year level. *Net Inflow* is defined as the difference between the inflow and outflow of inventors as measured above. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm; *HHI* is the industry Herfindahl-Hirschman Index. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS Regression Results			Second Stage Results of IV Regressions		
Variable	Net Inflow$_{t+1}$	Net Inflow$_{t+2}$	Net Inflow$_{t+3}$	Net Inflow$_{t+1}$	Net Inflow$_{t+2}$	Net Inflow$_{t+3}$
MQF	0.050***	0.049***	0.054***	0.560***	0.610***	0.655***
	(0.007)	(0.007)	(0.007)	(0.175)	(0.166)	(0.162)
Log(Assets)	0.073***	0.067***	0.060***	0.038***	0.031***	0.024**
	(0.003)	(0.003)	(0.003)	(0.013)	(0.012)	(0.011)
M/B	0.076***	0.080***	0.076***	-0.008	-0.017	-0.033
	(0.008)	(0.008)	(0.008)	(0.031)	(0.031)	(0.032)
ROA	0.050***	0.053***	0.050***	0.147***	0.152***	0.144***
	(0.016)	(0.015)	(0.016)	(0.039)	(0.037)	(0.035)
CAPEX/Assets	0.126**	0.106**	0.071	0.505***	0.498***	0.458***
	(0.050)	(0.048)	(0.050)	(0.148)	(0.136)	(0.130)
R&D/Assets	0.356***	0.257***	0.195***	0.243***	0.148***	0.096*
	(0.039)	(0.035)	(0.036)	(0.063)	(0.057)	(0.055)
Stock Return	-0.025***	-0.016***	-0.007*	0.000	0.012	0.021**
	(0.005)	(0.004)	(0.004)	(0.010)	(0.010)	(0.009)
Average Tenure	-0.004***	-0.003***	-0.002*	0.015**	0.017***	0.018***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.006)	(0.006)
HHI				0.450**	0.486**	0.370
				(0.210)	(0.222)	(0.245)
Observations	25,945	23,096	20,119	25,945	23,096	20,119
Adjusted R-squared	0.255	0.244	0.234			
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: The Effect of Management Quality on the Flow of High Quality and Low Quality Inventors

This table reports the OLS regression results of the net inflow of high-quality and net inflow of low-quality inventors for a firm in a given year on management quality factor (*MQF*) and tests the statistical difference of coefficient estimates. Panel A reports the effect of *MQF* on the net inflow of high-quality inventors and the net inflow of low-quality inventors. *Net Inflow of High* is the difference between the natural logarithm of one plus the number of high-quality inventors that move into the firm and the natural logarithm of one plus the number of high-quality inventors that move out of the firm in a given year; *Net Inflow of Low* is the difference between the natural logarithm of one plus the number of low-quality inventors that move into the firm and the natural logarithm of one plus the number of low-quality inventors that move out of the firm in a given year. Inventor quality is measured by the number of citations scaled by total number of patents that he has filed prior to the current year. An inventor is considered as a high-quality inventor if his prior track record of citations per patent is above the sample median. Otherwise, an inventor is considered as a low-quality inventor. Panel B reports the difference between the coefficient estimates using *Net Inflow of High* and *Net Inflow of Low* as dependent variables and tests their statistical differences. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: The Effect of MQF on Net Inflow of High-Quality and Low-Quality Inventors						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Net Inflow of $High_{t+1}$	Net Inflow of Low_{t+1}	Net Inflow of $High_{t+2}$	Net Inflow of Low_{t+2}	Net Inflow of $High_{t+3}$	Net Inflow of Low_{t+3}
MQF	0.053***	0.004***	0.053***	0.004***	0.056***	0.004***
	(0.007)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)
Ln(Assets)	0.078***	0.004***	0.071***	0.004***	0.064***	0.003***
	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)
M/B	0.079***	0.002***	0.084***	0.003***	0.080***	0.003***
	(0.009)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
ROA	0.049***	0.001	0.053***	0.001	0.050***	0.002*
	(0.016)	(0.001)	(0.016)	(0.001)	(0.016)	(0.001)
CAPEX/Assets	0.126**	0.004	0.115**	0.003	0.083	-0.003
	(0.051)	(0.004)	(0.050)	(0.004)	(0.051)	(0.004)
R&D/Assets	0.357***	0.013***	0.264***	0.008***	0.206***	0.008**
	(0.040)	(0.004)	(0.036)	(0.003)	(0.038)	(0.003)
Stock Return	-0.025***	-0.001**	-0.018***	-0.000	-0.008*	-0.001**
	(0.005)	(0.000)	(0.005)	(0.000)	(0.004)	(0.000)
Average Tenure	-0.004***	0.000	-0.003***	0.000	-0.002*	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	25,945	25,945	23,096	23,096	20,119	20,119
Adjusted R-squared	0.263	0.063	0.253	0.061	0.241	0.060
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Difference between the Effects of MQF on Net Inflow of High Quality and Low Quality Inventors			
	$Difference_{t+1}$	$Difference_{t+2}$	$Difference_{t+3}$
High-Low	0.050***	0.049***	0.052***
	(0.007)	(0.007)	(0.007)

Table 11: The Effect of Management Quality on the Average Quality of Incoming and Outgoing Inventors

This table reports the OLS and Instrumental Variable regression results of the average quality of incoming and outgoing inventors for a firm in a given year on management quality factor (*MQF*). Panel A reports the OLS regression results; Panel B reports the IV regression results using the same instrument variables as in Table 6, namely, the number of acquisitions of public targets made by established firms in the same industry (defined at 2-digit SIC code level) as the sample firm four and five years prior. *Incoming Quality* is the natural logarithm of one plus the average quality of all the inventors that move into the firm in a given year. *Outgoing Quality* is natural logarithm of one plus the average quality of all the inventors that move out of the firm in a given year. *Net Quality Change* is defined as the difference between *Incoming Quality* and *Outgoing Quality*. Inventor quality is measured by the number of citations scaled by total number of patents that he has filed prior to the current year. *Ln(Assets)* is the natural logarithm of the firm's total assets; *M/B* is Tobin's Q, defined as market value of assets divided by the book value of assets, where the market value of assets is computed as the book value of assets plus the market value of common stock less the book value of common stock; *ROA* is defined as operating income before depreciation divided by total assets; *CAPEX/Assets* is defined as capital expenditures divided by total assets; *R&D/Assets* is defined as research and development expenses divided by total assets; *Stock Return* is the firm's annual stock return; *Average Tenure* is the average number of years that each manager has worked as VP or higher in this firm; *HHI* is the industry Herfindahl-Hirschman Index. Constant, year fixed effects, 2-digit SIC industry fixed effects, and state fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. Coefficients and standard errors are multiplied by 100. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: OLS Regression Results									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Net Quality $Change_{t+1}$	Incoming $Quality_{t+1}$	Outgoing $Quality_{t+1}$	Net Quality $Change_{t+2}$	Incoming $Quality_{t+2}$	Outgoing $Quality_{t+2}$	Net Quality $Change_{t+3}$	Incoming $Quality_{t+3}$	Outgoing $Quality_{t+3}$
MQF	0.014***	0.042***	0.027***	0.014***	0.041***	0.027***	0.018***	0.043***	0.025***
	(0.005)	(0.006)	(0.003)	(0.005)	(0.006)	(0.003)	(0.005)	(0.006)	(0.003)
Log(Assets)	0.027***	0.055***	0.026***	0.024***	0.050***	0.024***	0.022***	0.045***	0.022***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)
M/B	0.024***	0.047***	0.020***	0.023***	0.046***	0.020***	0.022***	0.041***	0.018***
	(0.006)	(0.007)	(0.003)	(0.006)	(0.007)	(0.003)	(0.006)	(0.007)	(0.003)
ROA	0.012	-0.007	-0.013**	0.010	-0.008	-0.011**	0.014	0.001	-0.010**
	(0.012)	(0.014)	(0.005)	(0.011)	(0.013)	(0.005)	(0.012)	(0.013)	(0.005)
CAPEX/Assets	0.070**	0.040	-0.020	0.078**	0.069	0.004	0.030	0.043	0.011
	(0.033)	(0.041)	(0.017)	(0.035)	(0.043)	(0.017)	(0.035)	(0.043)	(0.017)
R&D/Assets	0.103***	0.090***	-0.009	0.056**	0.043	-0.008	0.039	0.040	-0.001
	(0.028)	(0.031)	(0.011)	(0.025)	(0.027)	(0.011)	(0.025)	(0.029)	(0.011)
Stock Return	-0.007*	-0.015***	-0.007***	-0.002	-0.006	-0.003*	-0.002	-0.002	-0.000
	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)
Average Tenure	-0.001	-0.001	0.000	-0.001	-0.001	-0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Observations	25,945	25,945	25,945	23,096	23,096	23,096	20,119	20,119	20,119
Adjusted R-squared	0.090	0.173	0.164	0.085	0.166	0.159	0.081	0.154	0.148
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Second Stage Results of IV Regressions									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Net Quality $Change_{t+1}$	Incoming $Quality_{t+1}$	Outgoing $Quality_{t+1}$	Net Quality $Change_{t+2}$	Incoming $Quality_{t+2}$	Outgoing $Quality_{t+2}$	Net Quality $Change_{t+3}$	Incoming $Quality_{t+3}$	Outgoing $Quality_{t+3}$
MQF	0.170	0.474***	0.293***	0.279***	0.586***	0.293***	0.395***	0.644***	0.223***
	(0.107)	(0.150)	(0.069)	(0.103)	(0.149)	(0.067)	(0.106)	(0.148)	(0.055)
Ln(Assets)	0.016**	0.026**	0.008	0.007	0.016	0.007	-0.001	0.009	0.010***
	(0.008)	(0.011)	(0.005)	(0.007)	(0.010)	(0.005)	(0.007)	(0.010)	(0.004)
M/B	-0.002	-0.024	-0.024*	-0.023	-0.049*	-0.026**	-0.046**	-0.069**	-0.018*
	(0.019)	(0.027)	(0.012)	(0.019)	(0.028)	(0.013)	(0.021)	(0.030)	(0.011)
ROA	0.041*	0.075**	0.038**	0.057**	0.089***	0.036**	0.073***	0.094***	0.021*
	(0.024)	(0.033)	(0.016)	(0.023)	(0.034)	(0.015)	(0.023)	(0.033)	(0.011)
CAPEX/Assets	0.188**	0.365***	0.179***	0.266***	0.452***	0.190***	0.274***	0.431***	0.138***
	(0.086)	(0.124)	(0.061)	(0.085)	(0.124)	(0.057)	(0.083)	(0.116)	(0.044)
R&D/Assets	0.068*	-0.005	-0.068***	0.004	-0.063	-0.060**	-0.024	-0.060	-0.034*
	(0.039)	(0.052)	(0.024)	(0.035)	(0.050)	(0.023)	(0.037)	(0.050)	(0.019)
Stock Return	0.000	0.006	0.006	0.012*	0.022**	0.010**	0.015**	0.026***	0.009***
	(0.007)	(0.009)	(0.004)	(0.007)	(0.009)	(0.004)	(0.007)	(0.009)	(0.003)
Average Tenure	0.005	0.015***	0.010***	0.009**	0.018***	0.009***	0.012***	0.020***	0.007***
	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.005)	(0.002)
HHI	-0.128	-0.075	0.105	-0.016	0.117	0.170*	0.052	0.171	0.142*
	(0.143)	(0.223)	(0.100)	(0.148)	(0.234)	(0.100)	(0.179)	(0.253)	(0.082)
Observations	25,945	25,945	25,945	23,096	23,096	23,096	20,119	20,119	20,119
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: The Effect of Management Quality on Highly Successful, Unsuccessful and Moderately Successful Innovations

This table reports OLS regression results of the number of very successful, unsuccessful and moderately successful patents on management quality factor (*MQF*). Panels A, B and C correspond to the regression results with dependent variables that are one, two and three years ahead, respectively. *Top 10%* is the natural logarithm of one plus the firm's number of patents that received cites within the top 10% among all patents in the same 3-digit patent class and application year; *No Cites* is the natural logarithm of one plus the number of patents that received no citation; *Moderate Cites* is the natural logarithm of one plus the number of patents that received at least one citation but below the top 10% among all patents. Columns (1)-(3) report the regression coefficients using *Top 10%*, *No Cites* and *Moderate Cites* as dependent variables, respectively; Columns (4)-(6) report and test the significance of difference between any two of the coefficient estimates in Columns (1)-(3). Control variables are the same as in Table 4 in all regressions and results are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Effect of Management Quality over One-year-ahead Patenting						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Top 10%$_{t+1}$	No Cites$_{t+1}$	Moderate Cites$_{t+1}$	Dif (1)-(2)	Dif (1)-(3)	Dif (2)-(3)
MQF	0.303***	0.147***	0.144***	0.156***	0.159***	0.003
	(0.038)	(0.018)	(0.020)	(0.023)	(0.022)	(0.008)
Observations	15,251	15,251	15,251			
Adjusted R-squared	0.406	0.384	0.428			
Control Variables	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			
Panel B: Effect of Management Quality over Two-year-ahead Patenting						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Top 10%$_{t+2}$	No Cites$_{t+2}$	Moderate Cites$_{t+2}$	Dif (1)-(2)	Dif (1)-(3)	Dif (2)-(3)
MQF	0.314***	0.152***	0.141***	0.162***	0.173***	0.011
	(0.040)	(0.019)	(0.020)	(0.024)	(0.024)	(0.009)
Observations	13,742	13,742	13,742			
Adjusted R-squared	0.408	0.381	0.424			
Control Variables	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			
Panel C: Effect of Management Quality over Three-year-ahead Patenting						
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Top 10%$_{t+3}$	No Cites$_{t+3}$	Moderate Cites$_{t+3}$	Dif (1)-(2)	Dif (1)-(3)	Dif (2)-(3)
MQF	0.321***	0.150***	0.136***	0.171***	0.185***	0.013
	(0.042)	(0.020)	(0.021)	(0.024)	(0.026)	(0.009)
Observations	12,118	12,118	12,118			
Adjusted R-squared	0.407	0.378	0.412			
Control Variables	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			

Internet Appendix (Not to Be Published)

Table A1: Robustness Test: The Effect of Management Quality on Corporate Innovation for Innovative Firms Only

This table reports the OLS regression results of corporate innovation on management quality factor (*MQF*) using innovative firms only. Innovative firms are defined as firms that have filed at least one patent application over the sample period of 1999-2009. Panels A, B and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Three-Year Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed over the next three years; *Three-Year Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed over the next three years; *Three-Year Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent received by the firm's patents filed over the next three years. Control variables are the same as in Table 4 in all regressions and results are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: The Effect of MQF on the Number of Patents				
	(1)	(2)	(3)	(4)
Variable	$Ln(Patents)_{t+1}$	$Ln(Patents)_{t+2}$	$Ln(Patents)_{t+3}$	Three-Year Ln(Patents)
MQF	0.134***	0.138***	0.137***	0.234***
	(0.016)	(0.017)	(0.017)	(0.027)
Observations	15,251	13,742	12,118	12,118
Adjusted R-squared	0.426	0.423	0.416	0.471
Control Variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: The Effect of MQF on the Total Number of Citations				
	(1)	(2)	(3)	(4)
Variable	$Ln(Citations)_{t+1}$	$Ln(Citations)_{t+2}$	$Ln(Citations)_{t+3}$	Three-Year Ln(Citations)
MQF	0.018***	0.018***	0.018***	0.056***
	(0.003)	(0.003)	(0.003)	(0.008)
Observations	15,251	13,742	12,118	12,118
Adjusted R-squared	0.292	0.285	0.273	0.350
Control Variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel C: The Effect of MQF on the Number of Citations per Patent				
	(1)	(2)	(3)	(4)
Variable	$Ln(Citations/Patent)_{t+1}$	$Ln(Citations/Patent)_{t+2}$	$Ln(Citations/Patent)_{t+3}$	Three-Year Ln(Citations/Patent)
MQF	0.000***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15,251	13,742	12,118	12,118
Adjusted R-squared	0.109	0.112	0.113	0.105
Control Variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table A2: Robustness Test: MQF without Team Size

This table reports the OLS regression results for corporate innovation with management quality factor without team size (*MQF-No Team Size*) as the key independent variable. *MQF-No Team Size* is defined in the same way as *MQF* except that we exclude team size in the common factor analysis. Panels A, B and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Three-Year Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed over the next three years; *Three-Year Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed over the next three years; *Three-Year Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent received by the firm's patents filed over the next three years. Control variables are the same as in Table 4 in all regressions and results are not reported to save space. Constant, year fixed effects, and 2-digit SIC industry fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: The Effect of MQF-No Team Size on the Number of Patents				
	(1)	(2)	(3)	(4)
Variable	Ln(Patents)$_{t+1}$	Ln(Patents)$_{t+2}$	Ln(Patents)$_{t+3}$	Three-Year Ln(Patents)
MQF-No Team Size	0.083***	0.077***	0.068***	0.151***
	(0.011)	(0.011)	(0.012)	(0.020)
Observations	27,688	24,519	21,250	21,250
Adjusted R-squared	0.375	0.368	0.359	0.434
Control Variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B: The Effect of MQF-No Team Size on the Total Number of Citations				
	(1)	(2)	(3)	(4)
Variable	Ln(Citations)$_{t+1}$	Ln(Citations)$_{t+2}$	Ln(Citations)$_{t+3}$	Three-Year Ln(Citations)
MQF-No Team Size	0.008***	0.007***	0.006***	0.025***
	(0.002)	(0.002)	(0.002)	(0.005)
Observations	27,688	24,519	21,250	21,250
Adjusted R-squared	0.242	0.236	0.227	0.292
Control Variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel C: The Effect of MQF-No Team Size on the Number of Citations per Patent				
	(1)	(2)	(3)	(4)
Variable	Ln(Citations/Patent)$_{t+1}$	Ln(Citations/Patent)$_{t+2}$	Ln(Citations/Patent)$_{t+3}$	Three-Year Ln(Citations/Patent)
MQF-No Team Size	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	27,688	24,519	21,250	21,250
Adjusted R-squared	0.136	0.134	0.131	0.132
Control Variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table A3: Robustness Test: Controlling for Industry×Year×State Fixed Effects

This table replicates the baseline regression results of corporate innovation on management quality factor (*MQF*) as in Table 4 controlling for industry×year×state fixed effects. Panel A, B and C report regression results with the number of patents, the total number of citations, and the number of citations per patent as dependent variables, respectively. *Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed in a given year; *Ln(Citations)* is the natural logarithm of one plus a firm's total adjusted number of citations received by the firm's patents filed in a year; *Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent. *Three-Year Ln(Patents)* is the natural logarithm of one plus the truncation-adjusted number of patents that a firm filed over the next three years; *Three-Year Ln(Citations)* is the natural logarithm of one plus the total adjusted number of citations received by the firm's patents filed over the next three years; *Three-Year Ln(Citations/Patent)* is the natural logarithm of one plus the adjusted number of citations per patent received by the firm's patents filed over the next three years. Control variables are the same as in Table 4 in all regressions and results are not reported to save space. Constant and industry×year×state fixed effects are included in all regressions. All standard errors are adjusted for clustering at the firm level and are reported in parentheses below the coefficient estimates. ***, **, and * represent statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: The Effect of MQF on the Number of Patents				
	(1)	(2)	(3)	(4)
Variable	Ln(Patents)$_{t+1}$	Ln(Patents)$_{t+2}$	Ln(Patents)$_{t+3}$	Three-Year Ln(Patents)
MQF	0.158***	0.158***	0.157***	0.280***
	(0.015)	(0.016)	(0.016)	(0.026)
Observations	25,945	23,096	20,119	20,119
Adjusted R-squared	0.370	0.365	0.351	0.434
Industry×Year×State FE	Yes	Yes	Yes	Yes

Panel B: The Effect of MQF on the Total Number of Citations				
	(1)	(2)	(3)	(4)
Variable	Ln(Citations/Patent)$_{t+1}$	Ln(Citations/Patent)$_{t+2}$	Ln(Citations/Patent)$_{t+3}$	Three-Year Ln(Citations/Patent)
MQF	0.020***	0.019***	0.019***	0.061***
	(0.002)	(0.002)	(0.003)	(0.007)
Observations	25,945	23,096	20,119	20,119
Adjusted R-squared	0.237	0.232	0.217	0.292
Industry×Year×State FE	Yes	Yes	Yes	Yes

Panel C: The Effect of MQF on the Number of Citations per Patent				
	(1)	(2)	(3)	(4)
Variable	Ln(Citations)$_{t+1}$	Ln(Citations)$_{t+2}$	Ln(Citations)$_{t+3}$	Three-Year Ln(Citations)
MQF	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	25,945	23,096	20,119	20,119
Adjusted R-squared	0.153	0.144	0.133	0.159
Industry×Year×State FE	Yes	Yes	Yes	Yes