Do General Managerial Skills Spur Innovation?*

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Abstract

We show that firms with chief executive officers (CEOs) who gain general managerial skills over their lifetime work experience produce more patents. We address the potential endogenous CEO-firm matching bias using firm-CEO fixed-effects and variation in the enforceability of non-compete agreements across states and over time during the CEO's career. Our findings suggest that generalist CEOs spur innovation because they have skills that can be applied elsewhere should innovation projects fail. We conclude that an efficient labor market for executives can promote corporate innovation by providing a mechanism of tolerance for failure.

JEL classification: G32, J24, O31

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1. Introduction

Innovation is a driving force in today's economy, but investing in new technologies, products, or services is risky and challenging. Decisions on research and development (R&D) budgets and the prioritization of research projects fall to top firm managers. In this paper, we ask whether a CEO's skill set is an important determinant of corporate innovation, and which CEO skills would be more valuable to produce innovation?

Managers draw on skills gained throughout a career when they make corporate decisions. Starting with Becker (1962), researchers have emphasized two types of managerial capital: general human capital (i.e., skills not specific to any organization and transferable across firms or industries) and firm-specific human capital (i.e., skills valuable only within an organization). We test the hypothesis that CEOs with more general skills foster innovation.[1]

Innovation carries a significant risk for top managers, as there are inherent uncertainties in going from concept to realization of actual profits. We conjecture that generalist CEOs are more likely to exploit innovative projects because they are less sensitive to the risk of termination, given their more diverse business experience compared to CEOs with focused professional experience. A generalist can move across industries more easily, as a failure in one place might not necessarily give a bad signal of ability in other industries. Thus, the broader set of outside options available to generalist CEOs and not to specialist CEOs acts as a labor market mechanism of tolerance for failure that can foster innovation. This mechanism can be an alternative to CEO contracts offering long-term compensation plans and job security. Manso (2011) shows that the optimal incentive mechanism that motivates innovation rewards long-term

[1] The growing importance of general skills has been linked to the increase in executive compensation over several decades (Murphy and Zabojnik (2007), Kaplan and Rauh (2013), and Frydman (2015)). Lazear (2005) shows that students who have diverse work and educational backgrounds are more likely to become entrepreneurs.

success but tolerates early failure. Lerner and Wulf (2007) and Tian and Wang (2014) provide evidence consistent with this idea.[2]

Additionally, a generalist CEO may take advantage of knowledge in a field beyond the company's current technological domain. A CEO who has worked in multiple positions, firms, and industries may accumulate general human capital that can be useful when a firm needs to invest in transformative change. For these reasons, we expect generalists to support innovation with a higher degree of originality and impact.

An alternative hypothesis is that specialist CEOs have more technical expertise that allows them to identify and promote innovation. Innovation tends to occur in highly specialized areas such as biotechnology and information technology where managers with an industry background may have an advantage. Managerial skills in a particular field can encourage specialists to invest in innovation, and make them better able to identify good projects. In fact, general managerial skills could be simply not unique but available from outside providers such as consultants. Therefore, it is an empirical question which CEO skills (general or specialist) matter for the quantity and quality of corporate innovation.

We examine the link between CEOs' general human capital and corporate innovation using the panel of Standard & Poor's (S&P) 1,500 firms over the 1993–2003 period. To measure general managerial skills, we use the *General Ability Index* (*GAI*) developed by Custódio, Ferreira, and Matos (2013), which captures five aspects of a CEO's professional career: past number of (1) positions, (2) firms, and (3) industries in which a CEO worked; (4) whether the executive held a CEO position at a different company; and (5) whether the CEO worked for a

[2] There is increasing empirical evidence of the link between firm policies and labor markets. Agrawal and Matsa (2013) show that firms choose conservative financial policies to mitigate workers' exposure to unemployment risk. Tate and Yang (2015) show that conglomerates redeploy labor to industries with better prospects.

conglomerate firm. The index of general managerial ability is the first factor of the principal components analysis of the five proxies.

We examine the productivity of a firm's research activities using patent-based metrics. We use the NBER patent database to measure the quantity and originality of a firm's research output (Hall, Jaffe, and Trajtenberg (2001)). We measure innovative activity by the number of patents that each firm files in a given year. We find that firms headed by generalist CEOs have significantly higher patent counts. A one-standard deviation increase in *GAI* is associated with an increase of 8% to 18% in patent counts. We also show that generalists acquire more patents through mergers and acquisitions (M&A) than specialist CEOs. We then measure the impact of a firm's patents by counting the citations that each patent receives from subsequent patents (i.e., cite-weighted patent counts). The results suggest that firms with generalist CEOs generate more citations counts. The effect is also important in economic terms: a one-standard deviation increase in *GAI* is associated with a 7% to 15% increase in citation counts.

We also study the effect of general managerial skills on the firm's innovation strategy. We find a positive relation between *GAI* and measures of the originality and generality of the patents, as indicated by a wider set of technological classes of patents cited and subsequent citing patents. Manso (2011) and Almeida, Hsu, and Li (2012) classify innovative strategies into exploitative (i.e., strategies that refine existing technologies) and exploratory (i.e., strategies that involve a more risky search for new technologies that can transform a business). We find that generalist CEOs engage more in exploratory than exploitative strategies relative to specialist CEOs.

Our findings are robust to the use of alternative econometric specifications (including negative binomial and Poisson regression models for count-dependent variables) and the inclusion of many firm-level controls such as firm size, capital intensity, growth opportunities, leverage, stock returns, and institutional ownership. Conditioning on R&D spending reduces the coefficient of *GAI* only slightly, suggesting that the main effect of general managerial skills is to alter the quality and productivity of R&D rather than simply stimulate more R&D.[3]

The findings are also robust to the inclusion of many CEO-level controls.[4] Galasso and Simcoe (2011) and Hirshleifer, Low, and Teoh (2012) show that psychological biases such as CEO overconfidence increase a manager's willingness to take riskier projects. We therefore control for an options-based CEO confidence measure in our tests (Malmendier and Tate (2005)). Acemoglu, Akcigit, and Celik (2015) show that younger CEOs engage in more creative innovations due to openness to disruption. Thus, we also control for CEO age, other observable characteristics such as CEO education, tenure, connections, and compensation structure (Barker and Mueller (2002), Coles, Daniel, and Naveen (2006), Bereskin and Hsu (2012), Coles, Li, and Wang (2013), Engelberg, Gao, and Parsons (2013), Faleye, Kovacs, and Venkateswaran (2014), Schmidt (2015)).

Our estimates may be biased due to endogenous matching between CEO and firm types. We address this concern in several ways. First, we use propensity score matching to compare firms run by generalists to otherwise similar firms run by specialists, and we continue to find a significant difference in innovation output. Unobserved firm or CEO variation may of course still be driving both innovation and general managerial ability. Therefore, we account for unobserved factors that are time-invariant using firm fixed-effects and firm-CEO fixed-effects. The firm-

[3] We also control for state-year and industry-year fixed effects to account for state and industry specific events that might affect innovation. For instance, Chava, Oettl, Subramanian, and Subramanian (2014) show that shocks to the local market power of banks have an impact on firm-level innovation. Mukherjee, Singh, and Zaldokas (2014) show that increases in state-level corporate tax rates have a negative impact on innovation.

[4] Researchers have examined whether corporate outcomes are affected by CEO characteristics (Kaplan, Keblanov, and Sorensen (2012), and Bertrand and Schoar (2003)). Fee, Hadlock, and Pierce (2013), however, cast doubt on the methodology for identifying managerial style effects on policy choices. They argue that CEO turnover events are endogenous and that managerial style changes are anticipated by corporate boards at the time of a CEO selection decision.

CEO fixed-effect estimator helps to rule out a number of alternative explanations because it solely relies on within firm-CEO variation. In this case, the identification only comes from CEOs for which the *GAI* changes during their tenure in the company. For example, GAI might change because the CEO gets a new board seat in a new firm or industry. Thus, the results suggest that the estimates are not driven by unobserved variation at the firm-CEO level that is also correlated with innovation.[5] The remaining concern is that time-variant unobserved factors at the firm-CEO level drive both innovation and CEO type. For example, an increase in *GAI* due to a new board seat might be associated with an increase in innovation due to other unobserved factors.

To further address omitted variables and reverse causality issues, we use instrumental variables methods. We use state-level labor laws on non-compete agreements as a source of exogenous variation in the generality of human capital of the CEO. Non-compete agreements are contracts that prevent employees from joining or creating a competing company after ending an employment contract. The enforceability of such contracts varies across U.S. states and over time. We use the Garmaise (2009) index on the enforceability of non-compete agreements during the career of a CEO as an instrument for *GAI*. The instrument is the average non-compete agreement enforcement index at the state-year level across all career positions the CEO has had in publicly traded firms (*Non-Compete Enforcement Index*). We expect the *Non-Compete Enforcement Index* to be positively related to *GAI*, because the enforcement of non-compete agreements limits within-industry manager transfers but enhances between-industry transfers (Garmaise (2009), Marx, Strumsky, and Fleming (2009)). Executives have an ex-ante incentive to accumulate more general skills if they work in states with stricter enforcement of non-compete clauses, so that they have more outside options and future mobility. We find the *Non-Compete*

[5] This approach also addresses the criticism by Fee, Hadlock, and Pierce (2013) that CEO turnover often coincides with a change in strategy such as investing more in innovation.

Enforcement Index to be positively and significantly correlated with *GAI.* The instrumental variable estimates suggest that general managerial skills affect innovation. The instrumental variables estimator, however, does not solve the endogenous firm-CEO match concern, as it explores exogenous variation in the *GAI* and not in the decision to appoint a generalist CEO. We rely on instrumental variables to address reverse causality concerns that remain as such when using the firm-CEO fixed-effect estimator.[6]

To explore the tolerance for failure channel, we investigate the difference in the value of outside options between generalist and specialist managers. In the presence of labor market geographic segmentation, Oyer's (2004) wage indexation theory implies that relevant outside opportunities for managers are likely to come from firms in the same region rather than from firms that are farther away. We use the tightness of the local labor market as a source of exogenous variation in the value of the outside options of managers (Kedia and Rajgopal (2009)). As the demand for managers is stronger in tight labor markets, managers are more likely to receive outside job offers from other firms in the region. Moreover, generalist managers should benefit more than specialists in tight labor markets because they have skills that are transferable across firms and industries. Consistent with this idea, we find that the relation between innovation and *GAI* is more pronounced in tight labor markets.

A second proxy for the value of outside options is the local beta, that is, the degree of comovement between a firm's stock price and stock prices of other firms in the same Metropolitan Statistical Area (Pirinsky and Wang (2006), Kedia and Rajgopal (2009)). Specialist executives are less likely than generalists to have outside job opportunities from other firms in

[6] Our results are also robust when we use a subsample of non-innovative industries and different tenure cutoffs. In these subsamples the CEO is less likely to have been hired with the goal of promoting innovation, and therefore selection concerns are mitigated.

the same region when their employer firm has low local betas. Consistent with this idea, we find a stronger relation between innovation and the *GAI* in the sample of firms with low local beta.

We complement this analysis by providing direct evidence of tolerance for failure in the market for CEOs. Using a sample of forced CEO turnovers, we show that generalists face lower costs and duration of unemployment spells. In fact, generalist takes less time to find a new position than a specialist after a forced turnover (an average of 8 months for a generalist versus 20 months for a specialist).

Finally, we address the question of whether innovation produced by CEOs with different levels of general ability adds to shareholder value. We show that new patents filed by generalist CEOs are associated with average abnormal announcement returns of about 17 basis points per patent (at the patent's grant date), which is significantly higher than that of specialist CEOs of 10 basis points. These results are consistent with Hall, Jaffe, and Trajtenberg (2005) and Kogan, Papanikolaou, Seru, and Stoffman (2015), who show that patent citations are positively correlated with firm valuation. Additionally, our results are not consistent with the possibility that generalist CEOs are "patent trolls" or simply better able to document the patents and go through the process of filling innovation. Patent trolls tend to file for specific and non-general type of patents, and do not necessarily invest in R&D, which is not the case for generalist CEOs.

Overall, we conclude that an efficient labor market for executives can promote innovation by serving as a mechanism of tolerance for failure. Generalist CEOs are more likely to exploit innovative growth opportunities because they have skills that can be applied elsewhere, should risky innovation projects fail. Our findings highlight the importance of general human capital and managerial skills in a modern knowledge-based economy where innovation is a key determinant of corporate success.

2. Data and measures

Our sample consists of a panel of CEO-firm-years of Standard & Poor's (S&P) 1,500 firms drawn from the EXECUCOMP database over 1993–2003. We manually match the executives in EXECUCOMP who are identified as CEOs in each year with the BoardEx database to obtain data on CEO prior professional experience. We then match firms in BoardEx where CEOs worked in the past to Compustat (U.S. firms) and Datastream (international firms) to obtain the standard industrial classification (SIC). We use information on all of a CEO's past positions, including those in non-S&P 1,500 firms.

To reassure that our findings are driven by a causal effect of managers on innovation, we restrict the sample to firm-years for which CEO-firm endogenous matching is likely to be less important, and in which CEOs are more likely to make an impact on the innovation process. Specifically, we restrict the sample to CEOs with at least three years of tenure, i.e., we exclude observations in which the CEO has been recently appointed.[7]

We use the NBER patent database to measure innovation for the S&P 1,500 firms (Hall, Jaffe, and Trajtenberg (2001, 2005)). The patent data are from the 2006 edition of the NBER patent database, which provides a link to EXECUCOMP by GVKEY. We control for firm characteristics using accounting data from Compustat, stock returns data from CRSP, and institutional ownership data from the Thomson CDA/Spectrum 13F Holdings. Variable definitions are provided in Table A1 in the Appendix.

The sample consists of S&P 1,500 firms in the intersection of EXECUCOMP, BoardEx, and the NBER patent database. Firms that operate in four-digit SIC industries without any filed

[7] In robustness tests, we will also present results with the sample of all CEOs and alternative tenure cutoffs.

patent in the sample period are excluded. As in previous literature, financial firms (SIC codes 6000-6999) and transportation and utilities (SIC codes 4000-4999) are also excluded. The final sample consists of 2,005 different CEOs with *GAI* from 8,419 firm-year observations (1,464 unique firms) between 1993 and 2003. We winsorize financial ratios at the bottom and top 1% levels.

2.1. Measuring general managerial ability

We use the *General Ability Index* (*GAI*) of Custódio, Ferreira, and Matos (2013), which captures the generality of a CEO's human capital based on lifetime work experience in publicly traded firms prior to the current CEO position. A CEO who worked in different organizational areas, for multiple firms, in different industries, in a conglomerate firm, or who has served as CEO previously is classified as having more generic skills.

The *GAI* of CEO *i* in year *t* is defined as:

$$GAI_{i,t} = 0.268\, X1_{i,t} + 0.312\, X2_{i,t} + 0.309\, X3_{i,t} + 0.218\, X4_{i,t} + 0.153\, X5_{i,t} \tag{1}$$

where $X1$ is the number of different positions that a CEO has had during his career; $X2$ is the number of firms where a CEO worked; $X3$ is the number of industries at the four-digit SIC level where a CEO worked; $X4$ is the a dummy variable that takes a value of one if a CEO previously held a CEO position at another firm; and $X5$ is a dummy variable that takes a value of one if a CEO worked for a multi-division firm (i.e., a company that reports more than one business segment). A CEO with a high *GAI* is likely to have acquired general skills that are transferable across firms and industries and to have more attractive outside options. The weights in equation (1) were obtained from extracting common components, using principal component analysis, from the five variables. Higher levels of general human capital are reflected in a higher value of the index. The index is standardized to have zero mean and a standard deviation of one.

A good example of a generalist executive is Louis Gerstner, who was CEO/Chairman of IBM over 1993–2002. He started his career at McKinsey & Company and had a diverse experience holding senior positions at American Express and being CEO of RJR Nabisco. Considered an outsider when he joined IBM, Gerstner was largely credited with turning around IBM's business, while John Akers, his predecessor, was an IBM lifer and more immersed in its corporate culture. Gerstner had a *GAI* score in the top 1% of the distribution at 3.11 when he joined IBM, with past experience in 11 positions, 10 firms, and 6 industries, as well as past experience as a top manager and at a conglomerate.

Under Gerstner, IBM stopped development of its own operating system and withdrew from the retail desktop PC market to focus on IT services where the tech industry was headed. Over the decade of his management, IBM produced a record-setting number of patents. IBM is fourth in the number of patents in our sample, with patent counts increasing from about 1,000 per year to more than 4,000. During this period, IBM was also in the top 1% of the distribution of citations.[8]

2.2. Measuring innovation

Our main tests are based on output-oriented measures of innovation. The first measure of innovation is the number of patent applications filed by a firm in a given year (*Patents*). One concern with this number is that patents are included in the database only if they are eventually granted, and there is on average a two-year lag between application and grant date. As the latest year available in the patent database is 2006, patents applied for in 2004 and 2005 may not show

[8] Bloomberg, "IBM Granted Most U.S. Patents for 20th Straight Year" (January 10, 2013).

up. Following Hall, Jaffe, and Trajtenberg (2001), we end our sample period in 2003 and include year fixed-effects in our regressions to address time truncation issues.

The second measure of innovation is the total number of citations to the patents that a firm applied for in a given year (*Citations*). Patent counts are an imperfect proxy of innovation success, as patents vary widely in their technological and economic relevance (Griliches, Hall, and Pakes (1987)). A common way to measure the relevance of a patent is by the number of citations it subsequently received. Hall, Jaffe, and Trajtenberg (2005) show that citations are positively related to firm valuation. Patents created near the ending year of the sample period have less time to accumulate citations. Therefore, citations suffer from a time truncation bias due to the finite length of the patent database. We address this concern by adjusting each patent's citation count by the average citation count of all patents in the same two-digit technological class and year (Hall, Jaffe, and Trajtenberg (2001, 2005)). The resulting variable is the sum of the adjusted citation count across all patents that a firm applied for in each year.

So far, the measures of innovation capture the intensity but not the technological knowledge base encompassed by the patents. The first measure is one minus the Herfindahl index of the citations made by the patents that a firm applied for in a given year across two-digit technological classes as proposed by Hall, Jaffe, and Trajtenberg (2001). This index looks at *backward* citations made by the firm in its patents. A high *Originality Index* (lower concentration) indicates that patents cited belong to a wider set of technological classes. The second measure is one minus the Herfindahl index of the citations received by the patents that a firm applied for in a given year across two-digit technological classes. This index looks at *forward* citations of the patents to measure the impact of the firm's innovation. A high *Generality Index* (lower concentration) indicates that a firm's patents are cited by subsequent patents across a wide range of fields.

The final set of measures examines a firm's innovation strategy. We classify firms' patent activity into exploratory and exploitative as proposed by Sorensen and Stuart (2000), Katila and Ahuja (2002), Benner and Tushman (2003), and Almeida, Hsu, and Li (2012). Firms focusing on their current areas of expertise are expected to produce more exploitative patents, while firms looking into new areas are expected to produce more exploratory patents. We construct proxies for exploitative and exploratory patents according to the extent to which a firm's new patents use current versus new knowledge. A firm's existing knowledge consists of its previous patent portfolio and the set of patents that have been cited by the firm's patents filed over the past five years. A patent is categorized as exploitative if at least 60% of its citations are based on current knowledge, and a patent is categorized as exploratory if at least 60% of its citations are based on new knowledge (i.e., citations not in the firm's existing knowledge base).[9] We then calculate the ratio of exploitative patents for a given firm-year as the number of exploitative patents filed in a given year divided by the number of all patents filed by the firm in the same year (*Exploitative Ratio*). The ratio of exploratory patents for a given firm-year is defined as the number of exploratory patents filed in a given year divided by the number of all patents filed by the firm in the same year (*Exploratory Ratio*). A higher ratio of exploitative patents suggests a more focused innovative strategy, while a higher ratio of exploratory patents suggests a more divergent innovative strategy.

2.3. Other explanatory variables

To explain innovation we include two main firm characteristics as controls in the base model,

[9] We obtain similar estimates using a cutoff of 80%, rather than 60%.

following Hall and Ziedonis (2001) and Aghion, Van Reenen, and Zingales (2013). Firm size is proxied by *Sales*. Capital intensity is proxied by the ratio of net property, plant, and equipment (PPE) to the number of employees (*Capital*/*Labor*). In robustness tests, we also consider specifications with additional and firm and CEO characteristics as controls.

3. General managerial ability and innovation

In this section, we test the hypothesis that CEOs with more general ability spur innovation.

3.1. Univariate tests

Table 1 shows summary statistics for corporate innovation, as well as CEO and firm characteristics. The average firm in the sample files 31 patents per year and subsequently receives 212 citations (raw count). It also engages more in exploratory than exploitative research: The average *Exploratory Ratio* is more than double the average *Exploitative Ratio*.

Table 2 compares sample means for specialist and generalist CEOs. A generalist CEO is defined as a top executive who has a *GAI* above the median in a given year. Firms with generalist CEOs versus specialist CEOs file more than double the patents (44 versus 19); and these patents generate more than twice as many subsequent citations (289 versus 138). The patents produced by generalists both make use of and produce more general knowledge, as measured by the *Originality Index* and the *Generality Index*, which are 40% and 47% higher for generalists versus specialists. Finally, firms with generalist CEOs seem to engage more in both exploratory and exploitative activities (albeit relatively more in exploratory) than firms with specialist CEOs.

The univariate tests suggest an economically meaningful difference in innovation output by firms with generalist CEOs. At this stage, however, we cannot attribute these differences just to general managerial ability, as other firm and CEO factors could potentially explain the patterns.

3.2. Patent filing and citations

Table 3 examines the relation between filed patents and the general ability of CEOs. The dependent variable is the logarithm of one plus the number of patents (*Patents*) in a given year. We control for industry (two-digit SIC)-year pair fixed-effects in column (1), and both industry-year and state-year fixed-effects in column (2). The industry-year and state-year fixed-effects control for innovation shocks that are specific to a given industry and year and a given state and year, respectively. Standard errors are clustered by firm to account for within-firm correlation.

We find that firms with generalist CEOs have higher patent counts. The estimates in columns (1) and (2) indicate that a one-standard deviation increase in *GAI* is associated with an additional 10%-11% in *Patents*. We then include firm fixed-effects to control for unobserved time invariant firm heterogeneity in column (3). The *GAI* coefficient is lower at about 8% but it is still economically and statistically significant. We include firm-CEO fixed-effects in column (4), which control for unobserved time-invariant CEO heterogeneity such as innate talent, mobility, or risk aversion in addition to firm heterogeneity. We find that the *GAI* coefficient estimate is stronger at about 18%. Column (4) indicates that CEO-firm endogenous matching is unlikely to explain our findings as the estimate is exclusively driven by within firm-CEO variation.

Table 4 presents estimates of regressions using measures of firm's innovation success. We run regressions similar to those in Table 3 and measure the success of innovation activity using the number of times a firm's patents are cited in subsequent patents. The dependent variable in column (1) is the logarithm of one plus citation counts adjusted for truncation bias (*Citations*). The *GAI* coefficient is positive and significant. The estimate in column (1) suggests that a one-standard deviation increase in *GAI* is associated with up to 10% more citations to patents produced by a firm. These results suggest that generalist CEOs produce patents with more citation counts, and the effect is both statistically and economically important. Results are similar when we also include state-year fixed-effects or firm fixed-effects in columns (2) and (3). The *GAI* coefficient estimate is stronger at about 15% when we rely solely on within firm-CEO variation. Overall, these results show a positive and significant relation between *GAI* and citation counts, which we take as an indication of the success and effectiveness of innovation activities.[10]

3.3. Innovation Strategy

We hypothesize that firms with generalist CEOs produce more novel innovation. Generalist CEOs have more outside options in the executive labor market, which can serve as a mechanism of tolerance for failure. Thus, generalist CEOs should be willing to take riskier growth opportunities. We test whether, while innovating, firms headed by generalist CEOs make use of a more diverse set of current patents, and whether the patents they produce are also cited by a more diverse set of technological classes. We run regressions similar to that in column (1) of Table 3, which includes industry-year fixed-effects.

The results in columns (1) and (2) of Table 5 using the *Originality Index* and the *Generality Index* suggest that firms with generalist CEOs make use of and produce a more diverse set of knowledge. The *Originality Index* (column (1)) increases by about 0.03 for a one-standard deviation increase in *GAI*. The effect is similar for the *Generality Index* (column (2)).

Manso (2011) differentiates exploratory and exploitative activities in the innovation process. We test the hypothesis that generalist CEOs are more willing to encourage innovation strategies that pursue both of these objectives. Still, we conjecture that for generalist CEOs the effect

[10] In robustness tests, we show estimates using raw citation count and alternative methods to adjust for truncation bias.

should be more pronounced for exploratory activities, which are intrinsically more uncertain. Columns (3) and (4) show the results. The dependent variables are the *Exploratory Ratio* and the *Exploitative Ratio*. The *GAI* coefficient is positive and significant for both the *Exploratory Ratio* and *Exploitative Ratio* dependent variables, but the relation between general skills and innovation is more pronounced for exploratory than exploitative innovation. The coefficient of *GAI* in the *Exploitative Ratio* regressions is positive and significant, but the coefficient in the *Exploratory Ratio* regressions is about three times higher.

Bena and Li (2014) find that firms with large patent portfolios and low R&D expenditures are acquirers, while firms with high R&D expenditures and slow growth in patent generation are targets. Thus, synergies from combining innovation efforts are important drivers of acquisitions. A possible interpretation of our results is that generalist CEOs promote in-house innovation, while specialists acquire innovation through mergers and acquisitions (M&A). If this is the case, specialists would not file patents but would still promote innovation. Even though generalists may have better negotiation skills, it could also be the case that specialists are better at evaluating the potential synergies of an acquisition, or at identifying good innovation targets. To address this possibility, we estimate a regression in which the dependent variable is the number of acquired patents by a firm in each year (*Acquired Patents*), as proxied by patents filed by the target firm in the previous five years prior to the M&A. Column (5) shows the result. The *GAI* coefficient is positive and significant but economically smaller at 2%. We conclude that the effect of generalists is present in both in-house patent production and externally acquired patents, but the effect is economically stronger in in-house patents.

Overall, the results are consistent with a conclusion that firms run by generalist CEOs produce more innovation because the top executive has been exposed to different industries, firms, and roles in the past. This might help CEOs promote R&D teams in the organization to think outside the box and bring solutions from other contexts to produce more original innovation.

4. The mechanism: the value of outside options

So far the results are consistent with the idea that generalist managers innovate more because their general skills and their potential mobility act as a mechanism of tolerance for failure. Next we explore exogenous variation in the value of outside options of CEOs to test this hypothesis. For this purpose, we use measures of local labor market conditions as a source of exogenous variation in the value of outside options.

In the presence of geographic segmentation, Oyer's (2004) wage indexation theory implies that relevant outside opportunities for an employee are likely to come from other firms in the same region rather than from firms that are farther away. A first proxy for the value of the outside options of managers is the tightness of a local labor market (Kedia and Rajgopal (2009)). As demand for workers is stronger in tight labor markets, managers are more likely to receive outside job offers from other firms in the region. Moreover, generalist managers should benefit more than specialists in tight labor markets because their skills are transferable across firms and industries. Thus, we expect the relation between innovation and *GAI* to be *more* pronounced in tight labor markets.[11]

A second proxy is the local beta, that is, the degree of comovement between a firm's stock price and stock prices of other firms in the Metropolitan Statistical Area (Pirinsky and Wang

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[11] Although there is less geographic segmentation of labor markets for top executives than for other workers, there is evidence indicating that geography does impact the CEO labor market (Knyazeva, Knyazeva and Masulis, (2013)). Yonker (2009) shows that geography affects both labor supply and labor demand in the market for CEOs, and Bouwman (2013) shows that geography affects CEO compensation.

(2006), Kedia and Rajgopal (2009)). Specialist managers are less likely to have outside job opportunities from firms in the same region when their firm has a low local beta. This is not the case with generalists, as they have skills that can be applied elsewhere. Thus, we expect to find a stronger relation between innovation and *GAI* in the sample of firms with low local beta.

Table 6 presents the results of regressions of *Patents* and *Citations* on general managerial effects, taking into account the value of outside options. The regressions include the same control variables and industry-year fixed effects as in previous tables. Panel A presents estimates of regression that include interaction between the *GAI* and *Tight Labor Market Dummy* as an explanatory variable. *Tight Labor Market Dummy* takes a value of one if the unemployment rate for a year in the Metropolitan Statistical Area (MSA) is less than the median unemployment rate for the MSA over the full sample period. The unemployment data are from the Bureau of Labor Statistics.

The interaction term coefficient is positive and significant in columns (1) and (2), indicating a stronger relation between corporate innovation (measured by patents or citations) in tight labor markets. We interpret this result as showing that better outside options of generalist versus specialist managers in tight labor markets act as a mechanism of tolerance for failure that makes generalists more willing to exploit innovative growth opportunities.

Panel B of Table 6 presents estimates of regressions that include an interaction between the *GAI* and *Low Local Beta Dummy* as an explanatory variable. The *Low Local Beta Dummy* takes a value of one if the local beta is below the top decile of the distribution, and zero otherwise. The local beta is estimated using a time series regression of monthly stock return on the return of the stock's corresponding MSA index (excluding the particular stock) as well as the return on the market portfolio and the stock's 48 Fama-French industry return over two different periods, 1993-1997 and 1998-2003 following Kedia and Rajgopal (2009). We require at least 24 non-missing monthly return observations for a stock, and that there be five stocks in the MSA to enter the regression. Returns in excess of monthly T-bill rates are taken from CRSP.

The interaction term coefficient is positive and significant in columns (1) and (2), which is consistent with the idea that the relation between innovation and *GAI* is attributable to the better outside options of generalist than specialist managers. The previous results are consistent with the idea that generalist CEOs are more willing to innovate because the labor market naturally acts as a mechanism of tolerance for failure.[12]

To further test if generalists do have a broader set of outside options that mitigate the costs incurred during unemployment spells, we study a sample of forced CEO turnover.[13] When we restrict the sample to forced CEO turnovers, we end up with a sample of 125 forced turnovers of which 83 are generalists and 42 specialists.

We find that the unconditional probability of finding any new position (board, non-board, executive or non-executive) in our panel of firms within the three year period following the turnover is 70% for generalist CEOs and 62% for specialist CEOs. If we consider only executive positions the probability of finding a new position in less than three years after the turnover is 41% for generalists and 36% for specialists. In the case of non-executive positions the difference in probability between generalists and specialists is even more striking at 58% and 31%, respectively.

We also compare the time that a generalist CEO who faces termination takes to find a new position compared to a specialist CEO. We find that generalists take on average 8 months to find

[12] Tate and Yang (2015) show that the workers of diversified firms and firms with conservative financial policies face lower costs and duration of their unemployment spells.

[13] We thank Dirk Jenter for providing us with the forced CEO turnover data used in Jenter and Lewellen (2010).

a new job, while specialists take 20 months. When we focus on executive positions, we find that generalists take on average 14 months to find a new position, while specialists take 16 months. In the case of non-executive positions the difference is much larger, as generalists find a new position in 13 months as compared to 42 months for specialists.

Although the sample of CEO forced turnovers is admittedly small and estimates are unconditional, the results are consistent with the idea that generalists face lower costs of their unemployment spell after facing termination. This supports the view that generalists are willing to innovate because they have skills transferable across firms and industry, which mitigate their exposure to unemployment risk.

5. Identification and additional results

There is some concern that our estimates could be biased due to endogenous matching between CEO types and firms. That is, there may be omitted factors correlated with both innovation and the generality of human capital of a CEO. Despite inclusion of firm-level controls and industry-year fixed-effects, the *GAI* coefficient might still be biased. We have addressed this concern at least partially by including firm fixed-effects to account for any unobservable firm characteristic that are time-invariant. Given that our sample period encompasses only 11 years, the fixed-effect estimator is quite effective in controlling for firm-level unobservable variables (as opposed, for instance, to including a firm fixed-effect in a panel of 50 years, where these unobservable variables are likely to change over such a long time).

However, firms might decide to change their policies, which might include start innovating, and also change their management team simultaneously. As a result, firms can choose a generalist CEO as part of a new business strategy and therefore the firm fixed-effect (or the CEO fixed-effect) estimator would not be enough to identify the effect of *GAI* on innovation. For this reason, we also use firm-CEO fixed-effects. This estimator relies only on within firm-CEO variation and therefore is able to rule out all the alternative explanations that are associated with time-invariant characteristics of the firm-CEO pair such as the quality of this match or the innate talent of the CEO. In fact, the identification only comes from CEOs for which *GAI* changes during their tenure in the company. This happens if, for instance, the CEO got an additional board seat, in a new firm that is eventually in a new industry.

Something that we cannot address with the firm-CEO fixed-effect estimator is the possibility that results are driven by time-variant characteristics of the firm-CEO pair, or reverse causality arguments, such that CEOs get additional board seats and become more generalist because the firm is more innovative.

5.1. Additional firm and CEO controls

Table 7 presents estimates of regressions using *Patents* and *Citations* as dependent variables. We run regressions similar to that in column (1) of Table 3 and column (1) of Table 4, which includes industry-year fixed-effects. We further control for firm characteristics (*Stock Return*, *Tobin's Q*, *PPE*, *ROA*, *Leverage*, *Cash*, *Firm Age*, *CAPEX*, *Institutional Ownership*, *Herfindahl Index, Governance Index*). Columns (1) and (3) show that the results remain similar when we include these additional firm-level (time varying) control variables.

We further control for additional CEO characteristics (*CEO Tenure*, *CEO Age*, *External Hire Dummy*, *CEO-Chair Dummy*, *MBA Dummy*). Coles, Daniel, and Naveen (2006) show that CEO incentives matter for firm risk taking. Therefore, we also include controls that take into account CEO incentives: *CEO Delta*, defined as the dollar change in a CEO's stock and option portfolio for a 1% change in stock price, measures the CEO's incentives to increases in stock price. *CEO Vega*, defined as the dollar change in a CEO's option holdings for a 0.01 change in standard deviation of returns, measures the risk-taking incentives generated by the CEO's option holdings. We calculate *CEO Delta* and *CEO Vega* values using the one-year approximation method of Core and Guay (2002).[14]

Hirshleifer, Low, and Teoh (2012) show that overconfident CEOs invest more in innovation, so we include a measure of CEO overconfidence as an additional explanatory variable. The overconfidence measure (*CEO Confidence Options*) uses data on option compensation following Malmendier and Tate (2005). This variable takes a value of one if a CEO postpones the exercise of vested options that are at least 67% in the money, and zero otherwise. The intuition is that it is optimal for risk-averse and undiversified executives to exercise their own-firm stock options early if an option is sufficiently in the money (Hall and Murphy (2002)).[15] We also control for CEO outside (school, social, and past professional) connections using the *CEO Rolodex* measure of Engelberg, Gao, and Parsons (2013).[16]

Columns (2) and (4) show that the results are similar when we include these additional CEO-level control variables. In particular, the results show that differences in CEO pay contracts do not explain the effect of general human capital on corporate innovation. We also conclude that overconfidence of CEOs and their general managerial ability are different mechanisms by which CEOs foster corporate innovation.

The tests so far use contemporaneous independent variables. In alternative specifications, we lag the independent variables by one, two, or three years. We also estimate regressions using changes for both the dependent variable and explanatory variables that focus directly on whether

[14] González-Uribe and Xu (2015) show that firm innovation cycle tends to match the length of the CEO contract.

[15] We thank David Hirshleifer, Angie Low, and Siew Hong Teoh for sharing data on proxies of CEO overconfidence. Additionally, we obtain similar findings using alternative measures of CEO overconfidence that rely on keyword searches of the text of press articles in Factiva, following Malmendier and Tate (2008).

[16] We thank Joseph Engelberg, Pengjie Gao, and Christopher Parsons for sharing data on CEO connections.

changes in the *GAI* subsequently affect changes in innovation. The results of these robustness checks (untabulated) confirm our main finding that generalist CEOs promote innovation.

5.2. Propensity score matching

To further address the endogenous matching concerns, we use propensity score matching to compare firms run by generalist CEOs (treatment group) with firms run by specialist CEOs (control group) with virtually no observable differences in firm and CEO characteristics. A generalist (specialist) CEO is defined as a CEO with a *GAI* above (below) the yearly median. We construct the control group of specialist CEOs using the nearest-neighbor method with scores given by a probit regression model of a dummy variable that takes a value of one for generalist CEOs and zero for specialist CEOs. The explanatory variables are CEO characteristics (*CEO Tenure*, *CEO Age*, *External Hire Dummy*, *CEO-Chair Dummy*, *MBA Dummy*) and firm characteristics (*Sales*, *Capital/Labor*, *Stock Return*, *Tobin's Q*, *PPE*, *ROA*, *Leverage*, *Cash*, *Firm Age*, *CAPEX*) and as well as industry and year dummies.

Panel A of Table 8 reports estimates of the probit regression model. CEOs with more accumulated general human capital tend to be older, to be hired from outside the firm, to hold a master of business administration (MBA) degree, and to have a shorter tenure than specialist CEOs. As expected, we find that firms with generalist CEOs are bigger. Panel B compares means of covariates between treated and control groups. There are no statistically significant differences with the exception of CEO tenure (the difference is 0.3 years), MBA dummy (the difference in frequency is 3 percentage points), and ROA (the difference is 0.6 percentage points) but these differences are not economically meaningful. We conclude that the treatment and control matched samples do not differ in terms of the observable covariates.

Panel C of Table 8 reports the average treatment effect (*ATT*) estimates, which are consistent with those obtained using panel regressions in Tables 3 and 4. Firms with generalist CEOs produce 25% more patents, which subsequently generate 24% more citations than firms with specialist CEOs. The propensity score matching results indicate that the potential assignment of generalist CEOs to more innovative firms (at least based on observable firm and CEO characteristics) does not explain our main findings.

5.3. Instrumental variable estimates

Despite the battery of tests run so far, it is not possible to conclude that causality runs from generalist managerial skills to corporate innovation. Ideally we would like to have exogenous variation in the decision to appoint a generalist or specialist CEO. We partially address the problem of endogenous match with the firm-CEO fixed-effect estimator but we still cannot rule out that innovation has an effect in *GAI*. To address this reverse causality issue we employ instrumental variables methods that exploit exogenous variation in the *GAI*. We make use of non-compete agreements as an instrument for the generality of human capital of the CEO. Non-compete agreements are contracts that prevent employees from joining or creating a competing company in their next job. Garmaise (2009) finds that 70% of the firms have non-compete agreements with their top executives. Bishara, Martin, and Thomas (2015) report that non-compete clauses are frequent in CEO contracts (79% of contracts have this sort of clause in the 1993-2010 period) with some restricting CEO's post-employment activities for more than four years. Additionally, there has been a significant trend toward the use of non-compete clauses in CEO contracts over time. These findings are consistent with other research on the frequency of noncompete provisions in entrepreneurs and CEOs contracts (Kaplan and Stromberg (2003), Gillan, Hartzell, and Parrino (2009)).

The enforceability of these clauses exhibits both cross-sectional variation (i.e., varying across

U.S. states) and time series variation (i.e., differing in the dates of adoption at the state level). The cross-sectional and time series variation of the instrument helps to rule out the concern that other state-level characteristics explain both *GAI* and innovation. We use the index on the enforceability of non-compete agreements in Garmaise (2009) during the career of the CEO as an instrument for *GAI*. The index takes values between a minimum of zero (e.g., California) and a maximum of nine (e.g., Florida after 1997).

We follow the career path of the CEO and create a *Non-Compete Enforcement Index* for each CEO-year observation, which is the average of the non-compete agreement enforcement index at the state-year level across all positions the CEO has had in publicly traded firms (the index is based on the location of the firm's headquarters).[17] This mitigates the concern that the CEO could strategically choose where to live to avoid non-compete clauses such as living in a neighboring state.

A good instrument should be correlated with the endogenous variable (*GAI*), but not with the error term on the dependent variables of interest (innovation). We expect the *Non-Compete Enforcement Index* to be positively related to *GAI* since the enforcement of non-compete agreements limits within-industry transfers and enhances between-industry transfers, contributing to the accumulation of general managerial skills. Consistent with this idea, Garmaise (2009) finds that executive job transfers within an industry decline with the level of non-compete enforceability faced by the firm, while transfers between industries rise.[18]

There is also a distinction between the ex-ante effects of non-compete agreements (human

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[17] Non-compete clauses are less frequent in non-executive position contracts. We obtain similar instrumental variable estimates (untabulated) when we calculate the *Non-Compete Enforcement Index* excluding past non-executive positions.

[18] Marx, Strumsky and Fleming (2009) show that non-compete enforcement constrains mobility more for inventors with firm-specific skills for those who specialize in narrow technical fields, by exploiting Michigan's inadvertent 1985 reversal of its non-compete enforcement policy as a natural experiment.

capital investment) and the ex-post effects (labor mobility) as suggested by Posner, Triantis, and Triantis (2004). Therefore, we expect executives to have an ex-ante incentive to accumulate more general skills in states with stronger enforcement of non-compete clauses. The idea is that if managers anticipate moving across industries they might decide to invest more in general human capital than in firm-specific knowledge to enable more outside options and facilitate ex-post mobility. Garmaise (2009) offers supporting evidence of this idea. In high-enforcement states, managers receive lower compensation and more of it in the form of salary, and firms invest less in capital-intensive production.

The second important assumption of the instrumental variables method is that the instrument should be a variable that can be excluded from the list of variables affecting the variable of interest (innovation). The exclusion restriction is likely to be satisfied in our setting as ex-ante career decisions of managers and their past positions are not likely to be directly correlated with the innovation policy of firms where they are currently top managers.[19]

Table 9 shows the results of the instrumental variables estimation for the *Patents* and *Citations* variables. The regressions include the same control variables as in Tables 3 and 4 as well as industry-year fixed-effects. Column (1) reports the first-stage regression estimates. As expected, we find that the *Non-Compete Enforcement Index* coefficient is positively and significantly correlated with *GAI* with a *t*-statistic of 5.1.

Columns (2) and (3) present second-stage regression estimates. The effect of *GAI* on the number of filed patents is positive and significant. The effect of *GAI* on citations is also positive.

[19] A remaining concern with the instrument is about the validity of the exclusion restriction because of location decisions of the CEO. There might be an unobserved CEO characteristic that is correlated both with current innovation and the *Non-Compete Enforcement Index*, which makes innovation linked to the instrument for other reasons than *GAI*. However, this concern is mitigated by the fact that the *Non-Compete Enforcement Index* is time varying within states.

The magnitude of the instrumental variables estimated coefficients is larger than for the ordinary least squares and fixed effects regressions.[20]

The enforceability of non-compete clauses is harder across states and typically has a limited geographic scope. The idea is that the contract might not have been enforced if the executive deliberately moved to another state in order to take a job in another firm in the same industry. To address this problem, we estimate the instrumental variables regression in Table 9 using a sample that excludes executives who moved to another state but stayed in the same industry at some point in their professional careers. The results (untabulated) remain consistent with a positive relation between innovation and *GAI*. Our results are also robust when we use the *Non-Compete Enforcement Index* of the firm as opposed to the employment history of the CEO. The tradeoff here is that the exclusion restriction is more likely to be violated in this setting.

In alternative, Garmaise (2009) uses the interaction of the *Non-Compete Enforcement Index* with the level of in-state competition, because the effect should be more pronounced when a firm is exposed to more intense in-state competition. In the case of considerable in-state competition, a high *Non-Compete Enforcement Index* will substantially reduce the probability that an executive will leave the firm and join a competitor. The limitation of using the interaction of the *Non-Compete Enforcement Index* with the level of in-state competition as instrument has to do with a possible violation of the exclusion restriction, because the level of in-state competition is likely to be related to innovation through channels other than general human capital. However, we continue to obtain similar estimates (untabulated) when we use this alternative instrument.

The effects of *GAI* on corporate innovation using instrumental variables methods are similar to those in our main regression tests, suggesting that the positive impact of general managerial

[20] The *GAI* measures general human capital with error and therefore ordinary least squares and fixed effects estimates are biased towards zero due to attenuation bias.

skills on innovation is robust to endogeneity concerns. Overall, the results support our hypothesis that the general ability of CEOs affects firm innovation output. We find that making the human capital of a CEO more general generates an increase in both number of filed patents and citations of those patents.

5.4. Innovation productivity and shareholder value

Another concern we address is that generalist CEOs file more patents and have more citations simply because they spend more on R&D. Table 10 controls directly for the level of R&D expenditures using the ratio of R&D expenditures to assets (*R&D*) in Panel A and cumulative R&D expenditures (*R&D Stock*) in Panel B.[21] When we control for *R&D* or *R&D Stock*, we still find economically and statistically significant *GAI* coefficients across all specifications. That is, results on the relation between innovation and general managerial ability are not explained by generalist CEOs spending more on R&D. This suggests that the primary effect of general managerial skills is to enhance the quality and the productivity of R&D rather than to simply stimulate more R&D.

To investigate whether innovation produced by generalists adds to shareholder value, we run an event study using a sample of patent grant announcements. We estimate cumulative abnormal returns (*CAR*) around patent grant dates using market-adjusted returns and market model (the CRSP value-weighted index is the benchmark). For the market model, we use a 260 trading days estimation window (–270, −11). We calculate the mean and median *CAR* over the three-day event window (−1, +1) around the announcement date separately for generalist CEOs (143,972

[21] Following Hall, Jaffe, and Trajtenberg (2005), *R&D Stock* is defined as $G_t = R_t + (1 - \delta)\, G_{t-1}$ where R is the R&D expenditure in year t and $\delta = 0.15$, the private depreciation rate of knowledge. Firm-years with missing R&D information are assigned a zero value.

patents) and specialist CEOs (71,386 parents).

Table 11 shows the results. We find positive and significant mean and median *CAR* in the sample of generalist CEOs, which is consistent with the notion that innovation by these managers adds to shareholder value. The mean *CAR* is 17 basis points per patent using market-adjusted returns and 7 basis points using the market model as a benchmark. The magnitudes of *CAR* estimates are in line with those in Kogan, Papanikolaou, Seru, and Stoffman (2015). The mean and median *CAR* for specialists are significantly lower than those of generalists. The difference in means is 6 basis points per patent using market-adjusted returns and 8 basis points using the market model. These results also help to rule out the concern that generalists are matched to non-practicing entities, commonly designated by "*patent trolls*". Cohen, Gurun, and Kominers (2015) show that the patents non-practicing entities assert are on average of lower quality from those asserted by practicing entities.

We also run regressions (untabulated) using Tobin's *Q* as the dependent variable and *GAI* as the main explanatory variable. As in Custódio, Ferreira, and Matos (2013), the *GAI* coefficient is positive but statistically insignificant. This insignificant relation between the *GAI* and firm performance may occur because performance is endogenous. However, this result does not mean that innovation is not affected by general human capital, or that innovation does not increase shareholder value. If there is an optimal matching based on CEO type (generalist versus specialist) and firm innovation policy, we will not observe cross sectional differences in firm performance based on CEO type. In other words, if we replaced a "well matched" generalist with a specialist CEO, only then we would observe a reduction in shareholder value.

Overall, the results support the view that innovation adds to shareholder value. The effect is more pronounced in the case of innovation produced by generalists than specialists. This is consistent with the evidence that patents produced by generalists have more impact and higher quality than those by specialists.

5.5. Robustness checks

Results of several robustness tests of our primary findings in Tables 3 and 4 are presented in the Internet Appendix. We discuss them briefly here.

We first present models using alternative measures of innovation. Although we focus on direct measures of innovation, we also examine the relation between stock return volatility and *GAI*. We run regressions similar to that in column (1) of Table 3 in which the dependent variable is the standard deviation of monthly stock returns which captures firms' risk-taking. Column (1) of Table IA.1 shows that the *GAI* is also associated with significant increases in stock return volatility. This evidence supports the interpretation that innovation is a risky activity.

We also examine whether firms run by generalist CEOs invest more in innovation activities, as measured by R&D expenditures, which is an input-oriented measure of innovation. We use the ratio of R&D expenditures to the book value of assets (*R&D*). Column (2) of Table IA.1 shows that *R&D* is positively and significantly associated with a CEO's general ability. A one-standard deviation in *GAI* is associated with a 0.5 percentage point higher *R&D*, which represents 13% of the average *R&D* of 3.8%. Additionally, column (3) shows that *GAI* is associated with significant increases in the dollar volume of R&D investment at about 14%.

An alternative measure of innovation productivity is total factor productivity (TFP). We estimate a firm-level regression in which the dependent variable is total sales, and the explanatory variables are the *GAI* and the logarithms of *Labor* (as proxied by number of employees) and *Capital* (as proxied by net property, plant, and equipment). Table IA.2 shows that *GAI* is positively associated with TFP. A one-standard deviation increase in *GAI* is associated with a 4% to 7% increase in TFP.

We then perform robustness checks related to the models of patent and citation counts. Hall, Jaffe, and Trajtenberg (2001) recommend using count-based models such as negative binomial and Poisson as alternatives to the ordinary least squares regression model.[22] In negative binomial and Poisson regressions in Table IA.3, columns (1) and (2), the dependent variable is *Patents*. The estimates confirm that *GAI* has an effect on patent counts between 18% and 22%.

Although we exclude firms operating in four-digit SIC industries with no patents, there are many firm-years with zero patents. To see if the results are driven by the jump from zero patents to at least one patent, we rerun the tests using the logarithm of the number of patents as dependent variable and therefore deleting observations with zero patents. The estimate in Table IA.3, column (3), is similar to our main results on the number of patents.

Table IA.4 presents robustness checks to the number of citations. In negative binomial and Poisson regressions, columns (1) and (2), the dependent variable is *Citations*. The estimates confirm that *GAI* has an effect between 14% and 19% on citation counts. We also rerun the tests using the logarithm of the number of citations as dependent variable (i.e., excluding observations with zero citations). The estimate in column (3) remains positive and statistically significant. A possible interpretation of the patent citation results is that firms with generalist CEOs simply have more citations because they file more patents. We address this concern using measures of citations per patent, which assess innovation success on a per-patent basis. In another test, we exclude self-citations at the firm level when calculating citation counts. The results in Table IA.4, columns (4) and (5), excluding self-citations and using per patent measures of innovation, respectively, remain similar. Column (6) presents estimates using raw citation counts as

[22] Different assumptions with respect to the properties of the error term generate different estimators. A Poisson model assumes the mean equals the variance, and a negative binomial model relaxes this assumption.

dependent variable, rather than adjusted citation counts. Column (7) presents estimates using an alternative method to adjust citation counts for truncation bias, which consists of multiplying each patent's citation count by a weighting index in Hall, Jaffe, and Trajtenberg (2001, 2005). The estimates confirm the main findings, and indicate that *GAI* has an effect on citation counts between 14% and 19%.

There are two distinct interpretations of the results. One is that general skills encourage managers to undertake risky endeavors such as innovation because they have more outside options should they fail. The other is that firms with promising opportunities for innovative projects appoint CEOs with general skills. In our main tests, we restrict the sample to CEOs with at least three years of tenure for which the effect of endogenous matching is likely to be less important. We now check whether results are robust to imposing a tenure cutoff from zero (i.e. the full sample of CEO-years) to five years. Table IA.5 summarizes the results. The *GAI* coefficient continues to be positively related to patent and citation measures to a similar degree, regardless of the tenure cutoff. These findings suggest that the relation between *GAI* and innovation is not primarily driven by the innovative firms' endogenous selection of managers with general skills.

One potential concern with the interpretation of the results is that generalist CEOs might be matched to firms in more innovative industries. To further address this concern, we split our sample into innovative industries (with median *Citations* for the industry in a given year of above the median across industries, using two-digit SIC codes) and non-innovative industries (with median *Citations* for the industry in a given year below the median across industries). Columns (1) and (2) of Table IA.6 shows that the positive relation between innovation and general managerial skills holds both for innovative and non-innovative industries in the case of patent counts. Columns (3) and (4) show that the effect of *GAI* on citation counts is actually stronger in non-innovative industries than in innovative industries. These findings support the idea that the effect of generalist skills on innovation does not come solely from the matching whereby firms in industries that have greater opportunities for innovation hire generalist CEOs.[23]

In fact, matching is unlikely to explain the positive relation between innovation and *GAI* in industries that have fewer opportunities for innovation. The choice of a CEO takes into account multiple CEO characteristics and not only the generality of his human capital. In this sense it is difficult for the firms to optimize along all these dimensions at the same time. Therefore, we expect more firms in the subsample of non-innovative industries to be out of equilibrium when it comes to level of innovation and *GAI*. This help us to better identify the effect of *GAI*.

A related concern is that generalist CEOs are more likely to have worked in innovative industries in the past, which is where they have acquired their ability to innovate. Because our findings are valid for both innovative and non-innovative industries, however, this is unlike to explain our findings.

We also perform some robustness checks related to the construction of the *GAI*. We use a dummy variable that takes a value of one for generalist CEOs (i.e., top executives with a *GAI* above the median in a given year) instead of a continuous variable. Results (untabulated) show that generalist CEOs produce 17% more patents and 14% more citations than specialist CEOs. Finally, separate regressions run for each individual component of the *GAI* in Table IA.7 show that all individual components are positively associated with innovation except past experience as CEO.

Finally, we also consider several other alternative explanations of a positive relation between

[23] These tests also show that our results hold even after including tech firms, which tend to be innovative and run by specialists CEOs.

innovation and *GAI*. A possibility is that generalist CEOs are exposed to lower risk of termination following poor firm performance, which could explain why they promote innovative opportunities. It is also possible that specialist CEOs might be less sensitive to bad performance as firms have fewer options available in the executive marketplace to replace them. When generalist CEOs have poor performance, firms can quickly replace them because there are more generalists available in the market. To address these possibilities, we estimate probit regressions in which the dependent variable is a dummy that takes a value of one if there is a CEO turnover in a given firm-year. We use two alternative samples: all turnovers and forced turnovers. The explanatory variables of interest are interactions between past firm accounting and stock performance (*ROA* and *Stock Return*) and the *GAI*. In untabulated results, we find a positive relation between the *GAI* and CEO turnover, but the relation does not seem to be triggered by poor firm performance. We find no difference in the sensitivity of CEO turnover to prior firm performance between generalist and specialist CEOs. The interaction term between the *GAI* and firm performance is not statistically significant in any of the specifications.

6. Conclusion

Our analysis of whether CEO general managerial skills matter for corporate innovation finds that CEOs who gain more human capital through their lifetime work experience promote more innovation in the organizations that they run. Patent-based metrics indicate that generalist CEOs promote innovation in the form of patents with higher impact. Generalist CEOs also incentivize firms to pursue more exploratory knowledge creation activities. We provide evidence consistent with a link from the generality of CEO human capital to the willingness to take risks using an instrument for general skills based on the state and time variation in the enforceability of non-compete agreements.

Our findings support the idea that generalist executives encourage firms to pursue risky innovation opportunities. While specialist CEOs have skills valuable only within an organization, generalist CEOs have skills that can be applied elsewhere. Thus, generalist CEOs have more outside options, which act as a labor market mechanism of tolerance for failure rather than internal mechanisms such as executive compensation plans. Given the growing importance of a knowledge-based economy, we provide new insight into why general managerial skills command a compensation premium in the executive labor market.

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Table 1
Summary Statistics

This table presents the mean, median, standard deviation, minimum, maximum, and number of observations for each variable. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993 - 2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix.

	Mean	Median	Standard deviation	Minimum	Maximum	Number of observations
Panel A: Innovation Measures						
Patents	31.1	1.0	154.5	0.0	4,339.0	8,419
Citations (raw)	212.1	0.0	1,307.0	0.0	45,512.0	8,419
Citations (adjusted)	31.4	0.0	161.3	0.0	4,146.0	8,419
Originality Index	0.421	0.525	0.358	0.000	0.945	8,419
Generality Index	0.389	0.450	0.354	0.000	0.944	8,419
Exploitative Ratio	0.139	0.000	0.238	0.000	1.000	8,419
Exploratory Ratio	0.333	0.000	0.390	0.000	1.000	8,419
Acquired Patents	1.6	0.0	27.7	0.0	1,380.0	8,419
Panel B: CEO Characteristics						
General Ability Index	-0.040	-0.189	0.957	-1.504	5.854	8,419
CEO Tenure	9.5	8.0	6.8	3.0	53.0	8,419
CEO Age	55.9	56.0	7.7	29.0	89.0	8,069
External Hire Dummy	0.391	0.000	0.488	0.000	1.000	8,419
CEO-Chair Dummy	0.706	1.000	0.456	0.000	1.000	8,419
MBA Dummy	0.298	0.000	0.457	0.000	1.000	8,419
CEO Delta	925.1	265.5	2,156.0	2.5	14,409.9	7,841
CEO Vega	102.5	38.9	171.2	0.0	971.7	7,841
CEO Confidence Options	0.678	1.000	0.467	0.000	1.000	7,600
CEO Rolodex	116.0	116.0	79.2	0.0	964.0	8,419
Non-Compete Enforcement Index	4.0	4.7	2.0	0.0	9.0	6,512
Panel C: Firm Characteristics						
Sales ($ million)	4,071.0	1,017.0	12,293.6	0.3	257,157.0	8,419
Capital/Labor	128.4	38.6	364.6	3.3	2,704.8	8,419
Stock Return	0.172	0.100	0.532	-0.775	2.208	7,483
Tobin's Q	2.3	1.7	1.6	0.8	8.9	8,410
PPE	0.389	0.227	0.519	0.015	3.158	8,419
ROA	0.148	0.150	0.100	-0.224	0.417	8,398
Leverage	0.218	0.209	0.174	0.000	0.828	8,392
Cash	0.142	0.059	0.180	0.001	0.751	8,418
Firm Age	22.5	16.0	19.5	0.0	78.0	8,400
CAPEX	0.066	0.051	0.054	0.000	0.286	8,333
Institutional Ownership	0.605	0.625	0.192	0.000	1.270	8,271
Herfindahl Index	0.075	0.053	0.072	0.026	0.904	8,271
Governance Index	9.3	9.0	2.7	2.0	18.0	6,402
R&D/Assets	0.038	0.010	0.060	0.000	0.271	8,419
R&D Stock ($ million)	373.9	20.1	1,765.0	0.0	38,611.8	8,419

Table 2
Innovation and General Managerial Ability: Univariate Tests

This table presents the mean of innovation measures for the sample of generalist CEOs (those with *General Ability Index* above the yearly median) and specialist CEOs (those with *General Ability Index* below the median in each year), the associated difference and its *p*-value. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix.

	Generalist CEOs	Specialist CEOs	Difference	p-value
Patents	44.3	18.5	25.8	0.000
Citations (raw)	289.1	138.2	150.9	0.000
Citations (adjusted)	42.9	20.4	22.5	0.000
Originality Index	0.492	0.352	0.140	0.000
Generality Index	0.465	0.316	0.149	0.000
Exploitative Ratio	0.161	0.118	0.043	0.000
Exploratory Ratio	0.390	0.279	0.111	0.000

Table 3
Patent Counts and General Managerial Ability

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) on the *General Ability Index*. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)
General Ability Index	0.113***	0.102***	0.077***	0.184***
	(3.077)	(2.725)	(2.733)	(2.789)
Log (*Sales*)	0.483***	0.515***	0.251***	0.188***
	(14.601)	(15.175)	(6.363)	(5.368)
Log (*Capital*/*Labor*)	0.201***	0.193***	0.084**	0.034
	(3.893)	(3.687)	(2.075)	(0.883)
Industry-year fixed-effects	Yes	Yes	Yes	Yes
State-year fixed-effects	No	Yes	No	No
Firm fixed-effects	No	No	Yes	No
Firm-CEO fixed-effects	No	No	No	Yes
Number of observations	8,419	8,297	8,419	8,419
R-squared	0.488	0.539	0.928	0.948

Table 4
Patent Citations and General Managerial Ability

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)
General Ability Index	0.096**	0.084**	0.066**	0.153**
	(2.558)	(2.204)	(2.132)	(2.203)
Log (*Sales*)	0.468***	0.505***	0.219***	0.164***
	(13.686)	(14.312)	(5.451)	(4.069)
Log (*Capital*/*Labor*)	0.205***	0.194***	0.087**	0.040
	(3.774)	(3.504)	(2.168)	(0.994)
Industry-year fixed-effects	Yes	Yes	Yes	Yes
State-year fixed-effects	No	Yes	No	No
Firm fixed-effects	No	No	Yes	No
Firm-CEO fixed-effects	No	No	No	Yes
Number of observations	8,419	8,297	8,419	8,419
R-squared	0.454	0.508	0.928	0.948

Table 5
Innovation Strategy and General Managerial Ability

This table presents estimates of ordinary least squares panel regressions of the *Originality Index*, *Generality Index*, *Exploratory Ratio, Exploitative Ratio*, and *Acquired Patents* on the *General Ability Index*. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Originality Index	*Generality Index*	*Exploratory Ratio*	*Exploitative Ratio*	*Acquired Patents*
	(1)	(2)	(3)	(4)	(5)
General Ability Index	0.031***	0.035***	0.028***	0.010**	0.021**
	(4.095)	(4.623)	(3.717)	(2.037)	(2.237)
Log (*Sales*)	0.057***	0.059***	0.032***	0.017***	0.059***
	(11.709)	(11.999)	(7.302)	(3.909)	(6.207)
Log (*Capital*/*Labor*)	0.021**	0.027***	0.013	0.014**	0.005
	(2.000)	(2.723)	(1.349)	(2.399)	(0.642)
Industry-year fixed-effects	Yes	Yes	Yes	Yes	Yes
Number of observations	8,419	8,419	8,419	8,419	8,419
R-squared	0.433	0.423	0.265	0.195	0.085

Table 6
Effect of Outside Options

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) and log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. *Tight Labor Market Dummy* is a dummy variable that takes a value of one if the unemployment rate for a year in the Metropolitan Statistical Area (MSA) is less than the median unemployment rate for the firm's MSA over the full sample period. *Low Local Beta Dummy* is a dummy that takes a value of one if the beta of a stock return on the return of the stock's corresponding MSA index is below the top decile of the distribution. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

Panel A: Tight Labor Markets		
	Log (1+*Patents*)	Log (1+*Citations*)
	(1)	(2)
General Ability Index	0.056	0.025
	(1.362)	(0.599)
Tight Labor Market Dummy	-0.059	-0.070
	(-1.081)	(-1.234)
General Ability Index × *Tight Labor Market Dummy*	0.086**	0.107***
	(2.200)	(2.679)
Log (*Sales*)	0.483***	0.468***
	(14.630)	(13.721)
Log (*Capital*/*Labor*)	0.200***	0.205***
	(3.883)	(3.762)
Industry-year fixed-effects	Yes	Yes
Number of observations	8,419	8,419
R-squared	0.489	0.455

Panel B: Local Beta		
	Log (1+*Patents*)	Log (1+*Citations*)
	(1)	(2)
General Ability Index	-0.137*	-0.135
	(-1.704)	(-1.538)
Local Beta Dummy	0.483***	0.470***
	(14.459)	(13.613)
General Ability Index × *Low Local Beta Dummy*	0.205***	0.210***
	(3.984)	(3.878)
Log (*Sales*)	-0.010	-0.088
	(-0.096)	(-0.841)
Log (*Capital*/*Labor*)	0.281***	0.260***
	(3.220)	(2.744)
Industry-year fixed-effects	Yes	Yes
Number of observations	8,419	8,419
R-squared	0.490	0.456

Table 7
Additional Firm and CEO Controls

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) and log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. Additional firm controls include *Stock Return*, *Tobin's Q*, *PPE*, *ROA*, *Leverage*, *Cash*, *Firm Age*, *CAPEX*, *Institutional Ownership*, *Herfindahl Index, Governance Index*. Additional CEO controls include *CEO Tenure*, *CEO Age*, *External Hire Dummy*, *CEO-Chair Dummy*, *MBA Dummy*, *CEO Delta*, *CEO Vega*, *CEO Confidence* Options, and *CEO Rolodex.* The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Log (1+*Patents*)		Log (1+*Citations*)	
	(1)	(2)	(3)	(4)
General Ability Index	0.086**	0.072**	0.082**	0.065*
	(2.419)	(2.001)	(2.253)	(1.764)
Log (*Sales*)	0.581***	0.445***	0.582***	0.433***
	(15.044)	(12.368)	(14.464)	(11.528)
Log (*Capital*/*Labor*)	0.230***	0.193***	0.232***	0.202***
	(4.403)	(3.688)	(4.329)	(3.642)
Industry-year fixed effects	Yes	Yes	Yes	Yes
Additional firm controls	Yes	No	Yes	No
Additional CEO controls	No	Yes	No	Yes
Observations	7,154	8,114	7,154	8,114
R-squared	0.564	0.505	0.531	0.470

Table 8
Propensity Score Matching

This table presents estimates of difference in the log of one plus number of patents (*Patent*) and log of one plus number of citations adjusted for truncation bias (*Citation*) between the treatment group (generalist CEOs) and the control group (specialist CEOs). The matched sample is constructed using a nearest-neighbor propensity score match with scores given by a probit model in which the dependent variable (*General Ability Dummy*) is a dummy variable that takes a value of one if a CEO has a *General Ability Index* above the median in a given year. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

Panel A: Probit (*Generalist Ability Dummy*)	
CEO Tenure	-0.038***
	(-14.225)
CEO Age	0.029***
	(11.508)
External Hire Dummy	0.377***
	(10.239)
CEO-Chair Dummy	0.369***
	(9.678)
MBA Dummy	0.411***
	(11.269)
Log (*Sales*)	0.250***
	(16.114)
Log (*Capital/Labor*)	-0.036
	(-1.450)
Stock Return	-0.013
	(-0.372)
Tobin's Q	0.009
	(0.634)
PPE	-0.022
	(-0.349)
ROA	-1.189***
	(-5.676)
Leverage	0.191*
	(1.702)
Cash	0.441***
	(3.284)
Firm Age	0.001
	(1.317)
CAPEX	-0.063
	(-0.137)
Industry-year fixed-effects	Yes
Number of observations	7,038

Table 8: continued

Panel B: Mean Differences in Covariates between Treated and Control				
	Treated	Control	Difference	p-value
CEO Tenure	8.690	8.371	0.319	0.028
CEO Age	57.229	57.019	0.210	0.213
External Hire Dummy	0.392	0.372	0.020	0.089
CEO-Chair Dummy	0.797	0.783	0.014	0.150
MBA Dummy	0.386	0.420	-0.034	0.004
Log (*Sales*)	7.492	7.466	0.026	0.493
Log (*Capital/Labor*)	3.869	3.836	0.033	0.224
Stock Return	0.167	0.150	0.017	0.168
Tobin's Q	2.182	2.119	0.063	0.080
PPE	0.361	0.348	0.013	0.201
ROA	0.143	0.137	0.006	0.007
Leverage	0.234	0.231	0.004	0.356
Cash	0.128	0.128	0.000	0.914
Firm Age	27.138	27.595	-0.457	0.375
CAPEX	0.060	0.061	-0.001	0.219

Panel C: Average Treatment Effect on the Treated	
Log (1+*Patents*)	Log (1+*Citations*)
(1)	(2)
0.250***	0.242***
(3.640)	(3.490)

Table 9
Instrumental Variables

This table presents estimates of instrumental variables methods using two-stage least squares (2SLS) panel regressions of the log of one plus number of patents (*Patents*) and log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. *Non-Compete Enforcement Index* is the average Garmaise (2009) non-compete agreement enforcement index at the state-year level across all positions the CEO has had in publicly traded firms. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	First Stage:	Second Stage:	
	General Ability Index	Log (1+*Patents*)	Log (1+*Citations*)
	(1)	(2)	(3)
General Ability Index		0.545**	0.489**
		(2.547)	(2.221)
Log (*Sales*)	0.169***	0.476***	0.468***
	(22.030)	(9.195)	(8.849)
Log (*Capital*/*Labor*)	0.008	0.255***	0.267***
	(0.590)	(4.150)	(4.116)
Non-Compete Enforcement Index	0.050***		
	(5.050)		
Industry-year fixed-effects	Yes	Yes	Yes
Number of observations	7,959	7,959	7,959
R-squared	0.176	0.459	0.436

Table 10
Innovation Productivity

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) and log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Log (1+*Patents*)		Log (1+*Citations*)	
	(1)	(2)	(3)	(4)
General Ability Index	0.066**	0.065**	0.056*	0.056*
	(2.157)	(2.143)	(1.775)	(1.769)
Log (*Sales*)	0.581***	0.556***	0.563***	0.537***
	(19.472)	(18.996)	(17.937)	(17.568)
Log (*Capital*/*Labor*)	0.164***	0.177***	0.172***	0.185***
	(3.704)	(3.979)	(3.623)	(3.880)
R&D/Assets	9.000***		8.960***	
	(13.038)		(12.634)	
Log (*R&D Stock*)		3.209***		3.175***
		(10.668)		(10.428)
Industry-year fixed-effects	Yes	Yes	Yes	Yes
Observations	8,419	8,419	8,419	8,419
R-squared	0.542	0.539	0.505	0.502

Table 11
Patent Grant Announcement Abnormal Returns and General Managerial Ability

This table shows mean and median cumulative abnormal returns (*CAR*) in percentage around the patent grant date announcement using a three-day event window (-1, 1) for the sample of generalist CEOs (those with *General Ability Index* above the yearly median) and specialist CEOs (those with *General Ability Index* below the median in each year). Abnormal returns are estimated using market-adjusted returns or a market model (CRSP value-weighted index is the benchmark) with coefficients estimated using a 260 trading days estimation window (-270, -11). The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. *p*-values of test of difference of means and Pearson chi-square of test of difference of medians are reported at the bottom of the table. *t*-statistics and Wilcoxon signed-rank test statistics are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Market-Adjusted Returns		Market Model		Number of
	Mean	Median	Mean	Median	Observations
Generalist CEOs	0.165	0.115	0.074	0.028	143,972
	(14.104)	(17.713)	(6.479)	(5.515)	
Specialist CEOs	0.104	-0.036	-0.001	-0.096	71,386
	(5.612)	(-4.581)	(-0.049)	(-1.183)	
Difference	0.061	0.151	0.075	0.124	
p-value	0.004	0.000	0.000	0.000	

Appendix

Table A1
Variable Definitions

Variable	Description
	Panel A: Innovation Measures
Patents	Number of patent applications by a firm in a given year (NBER patent database).
Citations	Total number of citations subsequently received by the patents that a firm applied for in a given year; each patent citation count is adjusted by the average citation count of all patents in the same two-digit technological class and year (NBER patent database).
Originality Index	One minus the Herfindahl index of the citations made by the patents that a firm applied for in a given year across two-digit technological classes (NBER patent database).
Generality Index	One minus the Herfindahl index of the citations received by the patents that a firm applied for in a given year across two-digit technological classes (NBER patent database).
Exploitative Ratio	Number of exploitative patents filed in a given year divided by the number of all patents filed by the firm in the same year; a patent is classified as exploitative if at least 60% of its citations are based on current knowledge (NBER patent database).
Exploratory Ratio	Number of exploratory patents filed in a given year divided by the number of all patents filed by the firm in the same year; a patent is classified as exploratory if at least 60% of its citations are based on new knowledge (NBER patent database).
Acquired Patents	Number of patents acquired through mergers, acquisitions, and reorganizations by a firm in a given year (patents filed by the target firm in the previous five years prior to the event) (NBER patent database).
	Panel B: CEO Characteristics
General Ability Index	First factor of applying principal components analysis to five proxies of general managerial ability: past *Number of Positions*, *Number of Firms*, *Number of Industries*, *CEO Experience Dummy*, and *Conglomerate Experience Dummy* (BoardEx).
General Ability Index Dummy	Dummy variable that takes a value of one if the CEO's general ability index is above the yearly median, and zero otherwise (BoardEx).
Number of Positions	Number of positions CEO has held in publicly traded firms (BoardEx).
Number of Firms	Number of firms CEO has worked in publicly traded firms (BoardEx).
Number of Industries	Number of industries (four-digit SIC) in which CEO has worked in publicly traded firms (BoardEx).
CEO Experience Dummy	Dummy variable that takes a value of one if CEO held a CEO position at another publicly traded firm, and zero otherwise (BoardEx).
Conglomerate Experience Dummy	Dummy variable that takes a value of one if CEO worked at a multi-segment publicly traded firm, and zero otherwise (BoardEx).
CEO Tenure	Number of years as CEO in the current position (BoardEx).
CEO Age	Age of CEO in years (BoardEx).
External Hire Dummy	Dummy variable that takes a value of one if CEO was hired from outside the firm, and zero otherwise (BoardEx).
CEO-Chair Dummy	Dummy variable that takes a value of one if CEO is also chair of the board, and zero otherwise (BoardEx).

Table A.1: continued

MBA Dummy	Dummy variable that takes a value of one if CEO has a MBA degree, and zero otherwise (BoardEx).
CEO Delta	Dollar change in a CEO's stock and option portfolio for a 1% change in stock price using the Core and Guay (2002) method.
CEO Vega	Dollar change in a CEO's option holdings for a 0.01 change in standard deviation of returns using the Core and Guay (2002) method.
CEO Confidence Options	Dummy variable that takes a value of one if a CEO postpones the exercise of vested options that are at least 67% in the money, and zero otherwise.
CEO Rolodex	Rolodex is the sum of school connections (attend the same university and have graduation years less than 2 years apart), social connections (members of the same social organization), and past professional connections (Engelberg, Gao, and Parsons (2013)).
Non-Compete Enforcement Index	Average Garmaise (2009) non-compete agreement enforcement index at the state level across all positions the CEO has had in publicly traded firms.
	Panel C: Firm Characteristics
Sales	Sales in millions of dollars (Compustat SALE).
Capital/Labor	Net property, plant, and equipment (Compustat PPENT) in millions of dollars divided by number of employees in thousands (Compustat EMP).
Stock Return	Annual stock return (Compustat (PRCC_F(t) / AJEX(t) + DVPSX_F(t) / AJEX(t)) / (PRCC_F(t-1) / AJEX_F(t-1))).
Tobin's Q	Assets plus market value of equity minus book value of equity divided by assets (Compustat (AT + CSHO × PRCC_F - CEQ) / AT)).
PPE	Net property, plant and equipment divided by total assets (PPENT / AT).
ROA	Earnings before interest and taxes divided by total assets (Compustat EBIT / AT).
Leverage	Total debt, defined as long-term debt plus debt in current liabilities, divided by total assets (Compustat (DLC + DLTT) / AT).
Cash	Cash and short-term investments divided by total assets (Compustat CHE / AT).
Firm Age	Number of years since a firm listed its shares (CRSP).
CAPEX	Capital expenditures divided by total assets (CAPX / AT).
Institutional Ownership	Shares held by institutional investors as a fraction of shares outstanding (Thomson CDA/Spectrum 13F Holdings).
Herfindahl Index	Herfindahl index calculated as the sum of squared market shares of firms' sales (Compustat SALE) at the two-digit SIC industry level.
Governance Index	Governance index of Gompers, Ishii, and Metrick (2003), which is based on 24 antitakeover provisions (IRRC).
R&D/Assets	Research and development expenses divided by total assets (Compustat XRD / AT).
R&D Stock	Cumulative R&D expenses assuming an annual depreciation rate of 15% (Compustat).
Tight Labor Market Dummy	Dummy variable that takes a value of one if the unemployment rate for a year in the MSA is less than the median unemployment rate for the MSA over the full sample period (Bureau of Labor Statistics).
Low Local Beta Dummy	Dummy variable that takes a value of one if the beta of a stock return on the return of the stock's corresponding MSA index is below the top decile of the distribution; local beta is estimated using a time series regression of monthly stock return on the return of the stock's corresponding MSA index (excluding the particular stock) as well as the return on the market portfolio and the stock's 48 Fama-French industry return over two different periods, 1993-1997 and 1998-2003, such that at least 24 non-missing monthly return observations for a stock and five stocks in the MSA enter the regression; returns are in excess of monthly T-bill rates (CRSP).

Internet Appendix for
"Do General Managerial Skills Spur Innovation?"

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Table IA.1
Alternative Measures of Innovation

This table presents estimates of ordinary least squares panel regressions of the standard deviation of returns (*Volatility*), ratio of R&D expenditures to assets (*R&D/Assets*), and the log of one plus cumulative R&D expenditures (*R&D Stock*) on the *General Ability Index*. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Volatility	*R&D/Assets*	Log(1+*R&D*)
	(1)	(2)	(3)
General Ability Index	0.003***	0.005***	0.139***
	(2.673)	(3.734)	(3.112)
Log (*Sales*)	-0.016***	-0.011***	0.487***
	(-20.802)	(-8.681)	(12.965)
Log (*Capital*/*Labor*)	0.004***	0.005***	0.308***
	(2.985)	(3.355)	(4.518)
Industry-year fixed-effects	Yes	Yes	Yes
Number of observations	8,419	8,419	8,419
R-squared	0.457	0.406	0.587

Table IA.2
Total Factor Productivity

This table presents estimates of ordinary least squares panel regressions of the log of total sales (*Sales*) on the *General Ability Index*. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)
General Ability Index	0.071***	0.050***	0.036**
	(3.400)	(2.761)	(1.970)
Log (*Labor*)	0.877***	0.599***	0.586***
	(52.180)	(25.411)	(25.055)
Log (*Capital*)		0.303***	0.278***
		(14.414)	(13.401)
Log (*R&D Stock*)			0.065***
			(8.311)
Industry-year fixed-effects	Yes	Yes	Yes
Number of observations	8,419	8,419	8,419
R-squared	0.821	0.853	0.858

Table IA.3
Patent Counts: Robustness

This table presents estimates of panel regressions of the number of patents (*Patents*) on the *General Ability Index*. Column (1) presents estimates of negative binomial regressions. Column (2) presents estimates of Poisson regressions. Column (3) presents estimates of a sample that excludes observations with zero patents. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Negative Binomial	Poisson	Exclude Zeros
Dependent variable	*Patents*	*Patents*	Log(*Patents*)
	(1)	(2)	(3)
General Ability Index	0.223***	0.184***	0.098***
	(3.904)	(6.942)	(4.156)
Log (*Sales*)	0.699***	0.885***	0.602***
	(18.230)	(48.744)	(35.329)
Log (*Capital*/*Labor*)	0.202**	0.596***	0.327***
	(2.034)	(9.605)	(8.960)
Industry-year fixed-effects	Yes	Yes	Yes
Number of observations	8,419	8,419	4,334
R-squared			0.492

Table IA.4
Patent Citations: Robustness

This table presents estimates of panel regressions of the number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. Column (1) presents estimates of negative binomial regressions. Column (2) presents estimates of Poisson regressions. Column (3) presents estimates of a sample that excludes observations with zero citations. Column (4) presents estimates of regressions of the number of citations excluding self-citations. Column (5) presents estimates of regressions of the number of citations per patent. Columns (6) and (7) present estimates of regressions of raw citation counts and adjusted citation counts using weighting index in Hall, Jaffe, and Trajtenberg (2001, 2005). The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

Dependent variable	Negative Binomial *Citations*	Poisson *Citations*	Exclude Zeros Log(*Citations*)	Exclude Self-Citations Log(1+*Citations*)	Citations per Patent Log(1+*Citations*)	Raw Citations Log(1+*Citations*)	Adjusted Citations Log(1+*Citations*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
General Ability Index	0.193***	0.137***	0.094***	0.137***	0.022***	0.144***	0.190***
	(3.220)	(4.655)	(3.791)	(3.038)	(2.853)	(3.046)	(3.408)
Log (*Sales*)	0.659***	0.866***	0.609***	0.534***	0.034***	0.555***	0.636***
	(14.911)	(39.815)	(33.425)	(13.583)	(5.624)	(13.310)	(13.144)
Log (*Capital*/*Labor*)	0.238**	0.649***	0.366***	0.231***	0.029**	0.242***	0.296***
	(1.969)	(7.219)	(9.350)	(3.529)	(2.571)	(3.440)	(3.538)
Industry-year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,419	8,419	4,906	8,419	8,419	8,419	8,419
R-squared			0.447	0.507	0.269	0.501	0.472

Table IA.5
Sample with Alternative CEO Tenure Cutoffs

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) and log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. The sample consists of EXECUCOMP firms for which chief executive officer (CEO) profile data are available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. The sample consists of EXECUCOMP firms for which chief executive officer (CEO) profile data are available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Log (1+*Patents*)			Log (1+*Citations*)		
	All CEOs	CEOs with Tenure > 3 years	CEOs with Tenure > 4 years	All CEOs	CEOs with Tenure > 3 years	CEOs with Tenure > 4 years
	(1)	(2)	(3)	(4)	(5)	(6)
General Ability Index	0.108***	0.113***	0.112***	0.099***	0.091**	0.085**
	(3.264)	(2.853)	(2.608)	(2.907)	(2.265)	(1.970)
Log (*Sales*)	0.484***	0.474***	0.466***	0.467***	0.458***	0.453***
	(15.055)	(13.986)	(13.387)	(13.991)	(13.227)	(12.797)
Log (*Capital*/*Labor*)	0.208***	0.196***	0.193***	0.215***	0.200***	0.196***
	(4.140)	(3.750)	(3.622)	(4.066)	(3.651)	(3.545)
Industry-year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	10,382	7,380	6,470	10,382	7,380	6,470
R-squared	0.484	0.489	0.494	0.448	0.457	0.464

Table IA.6
Innovative versus Non-Innovative Industries

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) and log of one plus number of citations adjusted for truncation bias (*Citations*) on the *General Ability Index*. An industry is classified as innovative if the median *Citation* for the industry (two-digit SIC) is above the median *Citations* across all industries in a given year. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	Log (1+*Patents*)		Log (1+C*itations*)	
	Innovative Industries	Non-Innovative Industries	Innovative Industries	Non-Innovative Industries
	(1)	(2)	(3)	(4)
General Ability Index	0.124**	0.123***	0.110*	0.104***
	(2.192)	(2.964)	(1.867)	(2.584)
Log (*Sales*)	0.581***	0.308***	0.567***	0.289***
	(13.534)	(6.399)	(13.006)	(5.866)
Log (*Capital*/*Labor*)	0.418***	0.064	0.460***	0.052
	(4.461)	(1.073)	(4.853)	(0.802)
Industry-year fixed-effects	Yes	Yes	Yes	Yes
Number of observations	3,973	4,446	3,940	4,479
R-squared	0.400	0.303	0.381	0.259

Table IA.7
General Managerial Ability Components

This table presents estimates of ordinary least squares panel regressions of the log of one plus number of patents (*Patents*) on the *General Ability Index* components. The sample consists of EXECUCOMP firms for which the chief executive officer (CEO) has at least three years of tenure and profile data available from BoardEx and patent data are available from the NBER database in the 1993-2003 period. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. Financial, transportation and utility firms are omitted. Variable definitions are provided in Table A1 in the Appendix of the paper. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** indicates significance at the 10%, 5% and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)
Number of Positions	0.052***				
	(4.906)				
Number of Firms		0.057***			
		(3.088)			
Number of Industries			0.051**		
			(2.505)		
Conglomerate Experience Dummy				0.125*	
				(1.873)	
CEO Experience Dummy					-0.039
					(-0.607)
Log (*Sales*)	0.460***	0.490***	0.492***	0.496***	0.504***
	(14.052)	(15.398)	(15.352)	(15.353)	(15.788)
Log (*Capital/Labor*)	0.202***	0.208***	0.209***	0.209***	0.208***
	(3.998)	(4.159)	(4.168)	(4.177)	(4.144)
Industry-year fixed-effects	Yes	Yes	Yes	Yes	Yes
Number of observations	8,419	8,419	8,419	8,419	8,419
R-squared	0.488	0.484	0.483	0.482	0.481