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http://orcid.org/0000-0003-4048-0312Cláudia Custódio, http://orcid.org/0000-0003-0537-2703Miguel A. Ferreira, http://orcid.org/0000-0003-3388-9515Pedro Matos

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# Do General Managerial Skills Spur Innovation?

**Cláudia Custódio,**[a,b,c] **Miguel A. Ferreira,**[b,c,d] **Pedro Matos**[c,e]

[a] Imperial College Business School, Imperial College London, London SW7 2AZ, United Kingdom; [b] Centre for Economic Policy Research, London EC1V 3PZ, United Kingdom; [c] European Corporate Governance Institute, B-1050 Brussels, Belgium; [d] Nova School of Business and Economics, 1099-032 Lisbon, Portugal; [e] Darden School of Business, University of Virginia, Charlottesville, Virginia 22906

**Contact:** c.custodio@imperial.ac.uk, http://orcid.org/0000-0003-4048-0312 (CC); miguel.ferreira@novasbe.pt, http://orcid.org/0000-0003-0537-2703 (MAF); matosp@darden.virginia.edu, http://orcid.org/0000-0003-3388-9515 (PM)

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**Abstract.** We show that firms with chief executive officers (CEOs) who gain general managerial skills over their lifetime of 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 noncompete agreements across states and over time during the CEO's career. Our findings suggest that generalist CEOs spur innovation because they acquire knowledge beyond the firm's current technological domain, and they have skills that can be applied elsewhere should innovation projects fail. We conclude that an efficient labor market for executives can promote innovation by providing a mechanism of tolerance for failure.

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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 typically fall to top firm managers. In this paper, we ask whether the skill set of a chief executive officer (CEO) is an important determinant of 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 with 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 his 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 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 fields 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. A CEO may become aware of developments in other domains and bring back ideas to his current firm if he has board seats in other firms and industries. For example, he may find out about a development at another firm that is directly applicable in his current firm or a potential synergy between unrelated divisions in his current firm. This is related to the idea that in a knowledge-based economy, one of the key challenges of the management is to create a firm without boundaries: replacing hierarchies with horizontal networks; linking together functional areas through cross-functional teams; and forming strategic alliances with suppliers, customers, and competitors (e.g., Hirschhorn and Gilmore 1992).[3] For these reasons, we expect generalist CEOs to support innovation with a higher degree of impact, originality, and generality, in particular by importing ideas from his exposure to other firms and industries.

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 and 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 innovation.

We examine the link between CEOs' general human capital and innovation using the panel of Standard & Poor's (S&P) 1500 firms over the period 1993–2003. To measure general managerial skills, we use the *General Ability Index* (*GAI*) developed by Custódio et al. (2013), which captures five aspects of a CEO's professional career: past number of (i) positions, (ii) firms, and (iii) industries in which he worked; (iv) whether he held a CEO position at a different company; and (v) whether he worked for a 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 R&D activities using patent-based metrics. We use the National Bureau of Economic Research (NBER) patent database to measure the quantity and quality of a firm's innovation output (Hall et al. 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 7%–19% in patent counts. We also show that generalists acquire more patents through mergers and acquisitions (M&As) 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 headed by generalist CEOs generate more citations. The effect is also important in economic terms: a one-standard-deviation increase in *GAI* is associated with a 6%–16% 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 et al. (2013) 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.

To explore the tolerance for failure mechanism, we investigate the difference in the value of outside options between generalist and specialist managers. 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.

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. Thus, a second proxy for the value of outside options is the local beta—that is, the degree of comovement between a firm's stock return and stock returns of other firms in the same metropolitan statistical area (MSA) (Pirinsky and Wang 2006, Kedia and Rajgopal 2009). Specialist executives are less likely than generalists to have outside job opportunities from other firms in the same region when their employer firm has low local betas. Consistent with this idea, we find a stronger relation between innovation and *GAI* in the sample of firms with low local beta. We obtain similar estimates if we use other measures of local competition for managers, including the number of peers located in the firm's MSA and the fraction of firms in the MSA that operate in the firm's industry.

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 cost and duration of unemployment spells than specialists. In fact, a 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).

To explore the new knowledge mechanism, we study the technological proximity (in the spirit of Jaffe 1986 and Balsmeier et al. 2017) between the firm's patents and the patents filed by another firm in which the CEO has a contemporaneous board seat. We find that the technological proximity between the firm where the CEO currently works and the firm in which he sits on the board of directors increases following his appointment. This result suggests that generalist CEOs are bringing new knowledge from other board positions. Note that the specialist CEOs might also bring ideas from his other experience into the current job at the same rate, but since the generalist has more breadth of experience, this might still translate into more ideas and innovation. In short, we provide direct evidence consistent with the new knowledge mechanism as well as the tolerance for failure/outside options mechanism. These two mechanisms, however, are not mutually exclusive, and both are supported by the evidence that generalist CEOs produce more patents and are more likely to go into new technological domains.

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, tangibility, investment, leverage, and family ownership.[4] 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.

The findings are also robust to the inclusion of CEO-level controls. Galasso and Simcoe (2011) and Hirshleifer et al. (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 et al. (2016) show that younger CEOs engage in more creative innovations because of openness to disruption. Thus, we also control for CEO age and other observable characteristics such as CEO education, tenure, connections, and compensation structure (Barker and Mueller 2002; Coles et al. 2006, 2017; Bereskin and Hsu 2012; Engelberg et al. 2013; Faleye et al. 2014; Schmidt 2015).[5]

Our estimates may be biased because of endogenous matching between CEO and firm types. Unobserved firm or CEO variation may be driving both innovation and general managerial ability. We account for unobserved factors that are time-invariant using firm fixed effects and firm–CEO fixed effects. The firm–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 comes from CEOs for which *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 our estimates are not driven by unobserved variation at the firm–CEO level that is also correlated with innovation.[6] 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 bias and reverse causality concerns, we use instrumental variables (IV) methods. We use state-level labor laws on noncompete agreements as a source of exogenous variation in the generality of human capital of the CEO. Noncompete 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 states and over time. We use the Garmaise (2009) index on the enforceability of noncompete agreements during the career of a CEO as an instrument for *GAI*. The instrument is the average noncompete agreement enforcement index at the state-year level across all career positions the CEO has had in publicly traded firms (*Noncompete Enforcement Index*). We expect the *Noncompete Enforcement Index* to be positively related to *GAI*, because the enforcement of noncompete agreements limits within-industry manager transfers and enhances between-industry transfers (Garmaise 2009, Marx et al. 2009). Executives have an ex ante incentive to accumulate more general skills if they work in states with stricter enforcement of noncompete clauses, so that they have more outside options and future mobility. As an alternative to the CEO career average index, we use the *Noncompete Enforcement Index* of the state and year of the first position of the CEO's career. By going further back in time, we alleviate the concern that the instrument violates the exclusion restriction because of correlation with the firm's current innovation through channels other than the CEO's general human capital.

We find that the *Noncompete Enforcement Index* is positively and significantly correlated with *GAI*. The instrumental variable estimates suggest that general managerial skills affect innovation. The instrumental variables estimator, however, does not fully solve the endogenous firm–CEO match concern, as it explores exogenous variation in *GAI* and not in the decision to appoint a generalist CEO.

Finally, we address the question of whether innovation produced by CEOs with different levels of general ability adds to firm valuation. 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 grant date), which is significantly higher than that of specialist CEOs of 10 basis points. These results are consistent with Hall et al. (2005) and Kogan et al. (2017), who show that patent citations are positively correlated with firm valuation. Additionally, our results do not support the possibility that generalist CEOs are "patent trolls" or simply better able to go through the process of filling innovation. Patent trolls tend to file for specific and nongeneral type of patents, and they do not necessarily invest more 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 success.

## 2. Data and Measures

Our sample consists of a panel of CEO–firm-years of S&P 1500 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 to Compustat (U.S. firms) and Datastream (international firms) to obtain the Standard Industrial Classification (SIC) of firms where CEOs worked. We use information on all of a CEO's past positions in publicly traded firms, including those in non-S&P 1500 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—that is, 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 1500 firms (Hall et al. 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 and stock market data from the Center for Research in Security Prices (CRSP). Variable definitions are provided in Table A.1 in the appendix.

The sample consists of S&P 1500 firms in the intersection of ExecuComp, BoardEx, and the NBER patent database. Firms that operate in four-digit SIC industries without any filed patent in the sample period are excluded. 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 *GAI* of Custódio et al. (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, or in a conglomerate firm or who has served as CEO previously is classified as having more general skills.

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

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

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 code level where a CEO worked, $X4$ is the a dummy variable that takes a value of 1 if a CEO previously held a CEO position at another firm, and $X5$ is a dummy variable that takes a value of 1 if a CEO worked for a multidivision firm (i.e., a company that reports more than one business segment). The weights in Equation (1) are 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 0 mean and a standard deviation of 1). Thus, 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.

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 industry was headed. Over the decade of his management, IBM produced a record-setting number of patents (Frier 2013). 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 up. Following Hall et al. (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 et al. 1987). A common way to measure the relevance of a patent is by the number of citations it subsequently received. Hall et al. (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 et al. 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. We also study measures of originality and generality of the patents filed by a given CEO. 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 et al. (2001). This index looks at *backward* citations made by the firm in its patents. A high *Originality Index* (lower concentration) indicates that the 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 Sørensen and Stuart (2000), Benner and Tushman (2003), and Almeida et al. (2013). 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 several firm characteristics as controls in the base model. Firm size is proxied by *Sales*. Capital intensity is proxied by the ratio of net property, plant, and equipment to the number of employees (*Capital/Labor*). We also control for growth opportunities (*Tobin's Q*), investment (*CAPEX*), ratio of debt to assets (*Leverage*), and family ownership (*Family Firm Dummy*). In robustness tests, we also consider specifications with additional firm and CEO characteristics as controls, which include market and accounting performance; firm age; institutional ownership; corporate governance measures; and CEO tenure, age, education, compensation, overconfidence, and network.

## 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 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 per year (44 versus 19), and these patents generate more than

**Table 1.** Summary Statistics

| | Mean | Median | Standard deviation | Minimum | Maximum | Number of observations |
|---|---|---|---|---|---|---|
| | | | Panel A: Innovation measures | | | |
| *Patents* | 31.10 | 1.00 | 154.50 | 0.00 | 4,339.00 | 8,419 |
| *Citations* (raw) | 212.10 | 0.00 | 1,307.00 | 0.00 | 45,512.00 | 8,419 |
| *Citations* (adjusted) | 31.40 | 0.00 | 161.30 | 0.00 | 4,146.00 | 8,419 |
| *Originality Index* | 0.32 | 0.00 | 0.35 | 0.00 | 0.95 | 8,419 |
| *Generality Index* | 0.26 | 0.00 | 0.33 | 0.00 | 0.94 | 8,419 |
| *Exploitative Ratio* | 0.14 | 0.00 | 0.24 | 0.00 | 1.00 | 8,419 |
| *Exploratory Ratio* | 0.33 | 0.00 | 0.39 | 0.00 | 1.00 | 8,419 |
| *Acquired Patents* | 1.56 | 0.00 | 27.67 | 0.00 | 1,380.00 | 8,419 |
| *Technological Proximity-All Positions* | 0.07 | 0.00 | 0.19 | 0.00 | 1.00 | 8,419 |
| *Technological Proximity-Current Positions* | 0.02 | 0.00 | 0.12 | 0.00 | 1.00 | 8,419 |
| | | | Panel B: CEO characteristics | | | |
| *General Ability Index* | −0.040 | −0.189 | 0.957 | −1.504 | 5.854 | 8,419 |
| *Noncompete Enforcement Index* | 4.00 | 4.70 | 2.00 | 0.00 | 9.00 | 6,512 |
| | | | Panel C: Firm characteristics | | | |
| *Sales* | 4,071.00 | 1,017.00 | 12,293.60 | 0.30 | 257,157.00 | 8,419 |
| *Capital/Labor* | 128.40 | 38.60 | 364.60 | 3.30 | 2,704.80 | 8,419 |
| *Tobin's Q* | 2.29 | 1.72 | 1.62 | 0.80 | 8.89 | 8,410 |
| *PPE* | 0.39 | 0.23 | 0.52 | 0.02 | 3.16 | 8,419 |
| *CAPEX* | 0.07 | 0.05 | 0.05 | 0.00 | 0.29 | 8,333 |
| *Leverage* | 0.22 | 0.21 | 0.17 | 0.00 | 0.83 | 8,392 |
| *Family Firm Dummy* | 0.29 | 0.00 | 0.45 | 0.00 | 1.00 | 8,419 |

*Notes.* 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 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 A.1 in the appendix.

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 55% and 66%, respectively, 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.

**Table 2.** Innovation and General Managerial Ability: Univariate Tests

| | Generalist CEOs | Specialist CEOs | Difference | *p*-Value |
|---|---|---|---|---|
| *Patents* | 44.300 | 18.500 | 25.800 | 0.000 |
| *Citations* (raw) | 289.100 | 138.200 | 150.900 | 0.000 |
| *Citations* | 42.900 | 20.400 | 22.500 | 0.000 |
| *Originality Index* | 0.391 | 0.252 | 0.139 | 0.000 |
| *Generality Index* | 0.326 | 0.196 | 0.130 | 0.000 |
| *Exploitative Ratio* | 0.161 | 0.118 | 0.043 | 0.000 |
| *Exploratory Ratio* | 0.390 | 0.279 | 0.111 | 0.000 |
| *Technological Proximity-All Positions* | 0.113 | 0.026 | 0.087 | 0.000 |
| *Technological Proximity-Current Positions* | 0.041 | 0.009 | 0.032 | 0.000 |

*Notes.* 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 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 A.1 in the appendix.

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 the two-digit SIC industry-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*

**Table 3.** Patent Counts and General Managerial Ability

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *General Ability Index* | 0.105*** | 0.093** | 0.073** | 0.189*** | 0.163** |
| | (2.838) | (2.474) | (2.568) | (2.816) | (2.472) |
| log(*Sales*) | 0.515*** | 0.549*** | 0.286*** | 0.225*** | 0.212*** |
| | (15.980) | (16.769) | (6.542) | (5.949) | (5.429) |
| log(*Capital*/*Labor*) | 0.199*** | 0.157*** | 0.041 | 0.006 | −0.012 |
| | (4.077) | (2.975) | (0.925) | (0.144) | (−0.264) |
| *Tobin's Q* | 0.143*** | 0.118*** | 0.008 | 0.001 | −0.004 |
| | (7.068) | (5.961) | (0.946) | (0.115) | (−0.447) |
| *PPE* | 0.058 | 0.238* | 0.209*** | 0.170*** | 0.177*** |
| | (0.453) | (1.822) | (3.711) | (3.208) | (2.969) |
| *CAPEX* | −0.250 | −0.521 | −0.183 | −0.221 | −0.191 |
| | (−0.369) | (−0.755) | (−0.743) | (−0.955) | (−0.798) |
| *Leverage* | −0.670*** | −0.677*** | −0.027 | −0.070 | −0.145 |
| | (−3.209) | (−3.371) | (−0.244) | (−0.612) | (−1.249) |
| *Family Firm Dummy* | −0.122 | −0.118 | 0.035 | 0.000 | −0.033 |
| | (−1.575) | (−1.565) | (0.464) | (0.005) | (−0.448) |
| Industry-year fixed effects | Yes | Yes | Yes | Yes | Yes |
| State-year fixed effects | No | Yes | No | No | Yes |
| Firm fixed effects | No | No | Yes | No | No |
| Firm–CEO fixed effects | No | No | No | Yes | Yes |
| Number of observations | 8,297 | 8,175 | 8,297 | 8,297 | 8,175 |
| $R$-squared | 0.509 | 0.555 | 0.138 | 0.150 | 0.221 |

*Notes.* This table presents estimates of OLS panel regressions of the log of one plus the number of patents (*Patents*). The sample consists of ExecuComp firms for which the 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 A.1 in the appendix. Robust $t$-statistics adjusted for firm-level clustering are reported in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

is associated with an additional 9%–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 7% but is still economically and statistically significant. We include firm–CEO fixed effects in columns (4) and (5), 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 16%–19%. Thus, CEO–firm endogenous matching is unlikely to explain our findings as these estimates are exclusively driven by within-firm–CEO variation.

Table 4 presents estimates of regressions using measures of firm's innovation quality. 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 9% more citations to patents produced by a firm. These results suggest that generalist CEOs produce patents with more citations, and the effect is both statistically and economically important. Results are similar when we include state-year fixed effects or firm fixed effects in columns (2) and (3). The *GAI* coefficient estimate is stronger at 12%–16% when we rely solely on within firm–CEO variation in columns (4) and (5). Overall, these results show a positive and significant relation between *GAI* and citation counts, which is an indication of the success and effectiveness of innovation activities.[10]

### 3.3. Innovation Strategy

We also 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 firms headed by generalist CEOs make use of a more diverse set of current patents when innovating 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

**Table 4.** Patent Citations and General Managerial Ability

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *General Ability Index* | 0.089** | 0.077** | 0.062** | 0.158** | 0.117* |
| | (2.353) | (1.989) | (1.984) | (2.249) | (1.662) |
| log(*Sales*) | 0.500*** | 0.538*** | 0.256*** | 0.208*** | 0.203*** |
| | (15.001) | (15.793) | (5.829) | (4.797) | (4.504) |
| log(*Capital*/*Labor*) | 0.203*** | 0.160*** | 0.053 | 0.014 | −0.010 |
| | (4.116) | (2.996) | (1.185) | (0.292) | (−0.210) |
| *Tobin's Q* | 0.154*** | 0.128*** | 0.016 | 0.008 | 0.004 |
| | (7.369) | (6.199) | (1.519) | (0.811) | (0.367) |
| *PPE* | 0.024 | 0.194 | 0.180*** | 0.168** | 0.176** |
| | (0.188) | (1.478) | (2.639) | (2.324) | (2.162) |
| *CAPEX* | 0.255 | −0.057 | −0.217 | −0.251 | −0.173 |
| | (0.365) | (−0.080) | (−0.734) | (−0.940) | (−0.625) |
| *Leverage* | −0.679*** | −0.675*** | −0.002 | −0.074 | −0.101 |
| | (−3.260) | (−3.333) | (−0.018) | (−0.606) | (−0.808) |
| *Family Firm Dummy* | −0.135* | −0.127* | 0.092 | 0.052 | −0.016 |
| | (−1.731) | (−1.681) | (0.943) | (0.601) | (−0.174) |
| Industry-year fixed effects | Yes | Yes | Yes | Yes | Yes |
| State-year fixed effects | No | Yes | No | No | Yes |
| Firm fixed effects | No | No | Yes | No | No |
| Firm–CEO fixed effects | No | No | No | Yes | Yes |
| Number of observations | 8,297 | 8,175 | 8,297 | 8,297 | 8,175 |
| *R*-squared | 0.477 | 0.525 | 0.132 | 0.138 | 0.201 |

*Notes.* This table presents estimates of OLS panel regressions of the log of one plus number of citations adjusted for truncation bias (*Citations*). The sample consists of ExecuComp firms for which the 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 period 1993–2003. 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 A.1 in the appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

a more diverse set of knowledge. The *Originality Index* (column (1)) increases by 0.026 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 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 low R&D expenditures and large patent portfolios 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 M&As. If this were the case, specialists would not file patents but would still promote innovation. 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) of Table 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 that the effect is economically stronger in in-house patents.

## 4. Mechanisms

So far, the results are consistent with the idea that generalist managers innovate more because their skills and potential mobility act as a mechanism of tolerance for failure. In this section, we explore variation in the value of outside options of CEOs to more directly test this hypothesis. In addition, generalists have been exposed to different industries, firms, and roles. We conjecture

**Table 5.** Innovation Strategy and General Managerial Ability

| | *Originality Index* (1) | *Generality Index* (2) | *Exploratory Ratio* (3) | *Exploitative Ratio* (4) | *Acquired Patents* (5) |
|---|---|---|---|---|---|
| *General Ability Index* | 0.026*** | 0.021*** | 0.028*** | 0.006 | 0.020** |
| | (3.752) | (3.413) | (3.685) | (1.357) | (2.165) |
| log(*Sales*) | 0.068*** | 0.072*** | 0.028*** | 0.020*** | 0.065*** |
| | (13.704) | (15.293) | (6.031) | (5.103) | (6.137) |
| log(*Capital/Labor*) | 0.039*** | 0.038*** | 0.040*** | 0.012* | −0.002 |
| | (4.176) | (4.577) | (4.065) | (1.815) | (−0.237) |
| *Tobin's Q* | 0.015*** | 0.015*** | 0.004 | 0.019*** | 0.023*** |
| | (3.790) | (4.058) | (1.059) | (5.891) | (3.508) |
| *PPE* | −0.028 | −0.017 | −0.084*** | 0.017 | 0.055*** |
| | (−1.175) | (−0.866) | (−3.724) | (1.013) | (3.174) |
| *CAPEX* | −0.206 | −0.082 | −0.327** | −0.127 | −0.243* |
| | (−1.579) | (−0.678) | (−2.242) | (−1.534) | (−1.798) |
| *Leverage* | −0.101** | −0.097*** | −0.071* | −0.028 | −0.097** |
| | (−2.504) | (−2.659) | (−1.693) | (−0.830) | (−2.120) |
| *Family Firm Dummy* | −0.028* | −0.022 | −0.010 | −0.024** | −0.015 |
| | (−1.815) | (−1.568) | (−0.643) | (−2.485) | (−0.969) |
| Industry-year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 8,297 | 8,297 | 8,297 | 8,297 | 8,297 |
| *R*-squared | 0.425 | 0.439 | 0.271 | 0.212 | 0.094 |

*Notes.* This table presents estimates of OLS panel regressions of *Originality Index*, *Generality Index*, *Exploratory Ratio*, *Exploitative Ratio*, and *Acquired Patents*. The sample consists of ExecuComp firms for which the 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 period 1993–2003. 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 A.1 in the appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

that this exposure might help them to encourage R&D teams to think outside the box and bring solutions and knowledge from other contexts to produce more and better innovation.

### 4.1. Tolerance for Failure

We use measures of local labor market conditions as a source of variation in the value of outside options. The first proxy for the value of the outside options of managers is the tightness of the 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. Because it may also be the case that a generalist CEO's capacity to innovate more is higher during weak economic conditions, we complement this analysis using other proxies of the CEO's 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.[11] To test this idea, we use the local beta—that is, the degree of comovement between a firm's stock return and stock returns of other firms in the same MSA (Pirinsky and Wang 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* (columns (1)–(4)) and *Citations* (columns (5)–(8)) 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. Columns (1) and (5) present estimates of regression that include the interaction between *GAI* and *Tight Labor Market Dummy* as an explanatory variable. The *Tight Labor Market Dummy* takes a value of 1 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. The unemployment data are from the Bureau of Labor Statistics.

The interaction term coefficient is positive and significant in columns (1) and (5), indicating a stronger relation between innovation (measured by patents or citations) in tight labor markets. We interpret this result as showing that better outside options of generalist

**Table 6.** Effect of Outside Options

| | log(1 + *Patents*) | | | | log(1 + *Citations*) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *General Ability Index* | 0.053 | −0.153* | 0.003 | 0.031 | 0.024 | −0.155* | −0.042 | −0.001 |
| | (1.270) | (−1.932) | (0.053) | (0.598) | (0.560) | (−1.824) | (−0.702) | (−0.015) |
| *Tight Labor Market Dummy* | −0.057 | | | | −0.067 | | | |
| | (−1.041) | | | | (−1.191) | | | |
| *General Ability Index* × *Tight Labor Market Dummy* | 0.079** | | | | 0.099** | | | |
| | (2.046) | | | | (2.487) | | | |
| *Low Local Beta Dummy* | | −0.033 | | | | −0.109 | | |
| | | (−0.338) | | | | (−1.064) | | |
| *General Ability Index* × *Low Local Beta Dummy* | | 0.292*** | | | | 0.276*** | | |
| | | (3.376) | | | | (2.999) | | |
| *Number of Firms MSA-Industry* | | | 0.115*** | | | | 0.132*** | |
| | | | (3.359) | | | | (3.695) | |
| *General Ability Index* × *Number of Firms MSA-Industry* | | | 0.043* | | | | 0.055* | |
| | | | (1.649) | | | | (1.947) | |
| *Fraction MSA-Industry* | | | | 0.919** | | | | 1.058*** |
| | | | | (2.455) | | | | (2.736) |
| *General Ability Index* × *Fraction MSA-Industry* | | | | 0.696* | | | | 0.834** |
| | | | | (1.721) | | | | (2.016) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry-year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 8,297 | 8,297 | 8,109 | 8,109 | 8,297 | 8,297 | 8,109 | 8,109 |
| *R*-squared | 0.509 | 0.511 | 0.514 | 0.511 | 0.478 | 0.480 | 0.485 | 0.481 |

*Notes.* This table presents estimates of OLS panel regressions of the log of one plus number of patents (*Patents*) and log of one plus the number of citations adjusted for truncation bias (*Citations*). The sample consists of ExecuComp firms for which the 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 period 1993–2003. 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 A.1 in the appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

managers 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.

Columns (2) and (6) present estimates of regressions that include an interaction between *GAI* and *Low Local Beta Dummy* as an explanatory variable. The *Low Local Beta Dummy* takes a value of 1 if the local beta is below the top decile of the distribution and 0 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 industry (Fama–French 48-industry classification) return over two different periods, 1993–1997 and 1998–2003. We require at least 24 nonmissing monthly return observations for a stock and that there are 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 (2) and (6), which is consistent with the idea that the relation between innovation and *GAI* is attributable to the better outside options of generalist managers relative to specialist managers. The 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 show the robustness of the local beta variable, we use two other measures of the local competition for workers. These variables capture the extent of industry representation in the MSA and consequently the competition for local workers. Specifically, we use (i) the number of other firms in the firm's industry (two-digit SIC) that are also located in the firm's MSA (*Number of Firms MSA-Industry*) in columns (3) and (7), and (ii) the fraction of firms in the MSA that are in the firm's industry (two-digit SIC) (*Fraction MSA-Industry*) in columns (4) and (8). The interaction term coefficient is positive and significant in all of these regressions, which is consistent with the idea that outside options help to explain the relation between innovation and general managerial ability.

To further test whether 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, nonboard, executive, or nonexecutive) 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 restrict the sample to 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 nonexecutive positions, the difference in probability between generalists and specialists is even more striking, at 58% and 31%, respectively.

We then compare the time that a generalist CEO who faces termination takes to find a new position compared with a specialist CEO. We find that generalists take on average 8 months to find 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 nonexecutive positions, the difference is much larger, as generalists find a new position in 13 months when compared with 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 when facing termination. This supports the view that generalists are willing to innovate because they have skills transferable across firms and industry, which mitigates their exposure to unemployment risk.

### 4.2. New Knowledge

We use a measure of proximity between the technology classes of the patents of the firm in which a manager is currently the CEO and those of patents filed by another firm for which he is appointed to the board of directors. *Technological Proximity* ($P_{ijt}$), in the spirit of Jaffe (1986) and Balsmeier et al. (2017), represents the technological class overlap between the patents filed by firm $i$ in year $t$ and the patents filed by the set of firms $j$ in which the CEO has a board seat:

$$P_{ijt} = \sum_{k=1}^{K} f_{ikt} f_{jkt} \Bigg/ \left( \sum_{k=1}^{K} f_{ikt}^2 \cdot \sum_{k=1}^{K} f_{jkt}^2 \right)^{1/2}, \qquad (2)$$

where $f_{ikt}$ is the fraction of firms $i$'s patents that belong to patent class $k$ at time $t$, and $f_{jkt}$ is the fraction of patents filed by another firm in which the CEO has a (contemporaneous) board seat (we only consider the patents filed during the tenure of the CEO at these firms) that belong to patent class $k$ at time $t$; $P_{ijt}$ ranges between 0 and 1.

Table 7 presents the results of event-study regressions of *Technological Proximity* around the year of the CEO's appointment to a board seat at another firm. We test whether the *Technological Proximity* between the firm where he is currently the CEO and the firm where he is a board member increases following his appointment to the board of directors. The event window starts at year −3 before the appointment year and ends at year +1, +2, +3, +4, or +5 after the appointment year. Panel A presents the results of ordinary least squares

**Table 7.** Technological Proximity

| Window (years): | (−3, 1) | (−3, 2) | (−3, 3) | (−3, 4) | (−3, 5) |
|---|---|---|---|---|---|
| | | | Panel A: OLS | | |
| *Post Dummy* | 0.011** | 0.012** | 0.011** | 0.011** | 0.010* |
| | (2.124) | (2.425) | (2.172) | (2.024) | (1.765) |
| *Constant* | 0.056*** | 0.062*** | 0.065*** | 0.064*** | 0.068*** |
| | (2.865) | (2.992) | (2.993) | (2.938) | (2.993) |
| Number of observations | 4,882 | 5,719 | 6,430 | 7,009 | 7,448 |
| $R$-squared | 0.011 | 0.011 | 0.011 | 0.011 | 0.012 |
| | | | Panel B: Event fixed effects | | |
| *Post Dummy* | 0.009* | 0.011** | 0.010* | 0.009* | 0.009 |
| | (1.667) | (1.996) | (1.826) | (1.755) | (1.604) |
| Number of observations | 4,882 | 5,719 | 6,430 | 7,009 | 7,448 |
| $R$-squared | 0.806 | 0.793 | 0.781 | 0.776 | 0.770 |

*Notes.* This table presents estimates of OLS regressions and event fixed-effects regressions of *Technological Proximity* ($P_{ijt}$) around the year of the CEO's appointment to a board seat at another firm. *Post Dummy* is a dummy variable that takes a value of 1 in the year of the CEO's appointment and thereafter and 0 otherwise. The sample consists of ExecuComp firms for which the 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 period 1993–2003. 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 A.1 in the appendix. Robust $t$-statistics adjusted for firm-level clustering are reported in parentheses.

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(OLS) regressions, and panel B presents the results of event fixed-effects regressions (i.e., these regressions explore only within-firm pair variation). We find a statistically and economically significant increase in *Technological Proximity* following the CEO appointment as a board member at another firm. The estimated coefficient is 0.009–0.012, which represents about 10% of the average *Technological Proximity*.

These results support the new knowledge mechanism: a CEO can bring new ideas to his current firm from his board positions at other firms, which results in higher technological proximity between firms. However, the tolerance for failure and new knowledge mechanisms are not mutually exclusive, and both are supported by the evidence that generalist CEOs produce more patents and are more likely to go into new technological domains.

## 5. Identification and Additional Results

There is a concern that our estimates could be biased as a result of 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 the 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 to, for example, including a firm fixed effect in a panel of 50 years in which these unobservable variables are likely to change over such a long period).

However, firms might decide to change their policies and start innovating while also changing their management team. As a result, firms can choose a generalist CEO as part of a new business strategy, and therefore, the firm fixed-effect (or 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, we are able to rule out all of the alternative explanations that are associated with time-invariant characteristics of the firm–CEO pair such as the quality of the match or the innate talent of the CEO. In fact, the identification comes only from CEOs for which *GAI* changes during their tenure in the firm. This happens if, for example, the CEO got an additional board seat in a new firm that is in a different industry or in a conglomerate.

### 5.1. Instrumental Variable Estimator

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. 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 on *GAI*.

To address the reverse causality concern, we employ instrumental variables methods that exploit exogenous variation in *GAI*. We make use of noncompete agreements as an instrument for the generality of human capital of the CEO. Noncompete 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 noncompete agreements with their top executives. Bishara et al. (2015) report that noncompete clauses are frequent in CEO contracts (79% of contracts have this sort of clause in the period 1993–2010) with some restricting CEOs' postemployment activities for more than four years. Additionally, there has been a significant trend toward the use of noncompete clauses in CEO contracts over time. These findings are consistent with previous research on the frequency of noncompete provisions in entrepreneurs and CEOs contracts (Kaplan and Strömberg 2003, Gillan et al. 2009).

The enforceability of these clauses exhibits both cross-sectional variation (i.e., varying across 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 noncompete agreements in Garmaise (2009) during the career of the CEO as an instrument for *GAI*. The index takes values between a minimum of 0 (e.g., California) and a maximum of 9 (e.g., Florida after 1997).

We follow the career path of the CEO and create a *Noncompete Enforcement Index* for each CEO-year observation, which is the average of the noncompete 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).[14] This mitigates the concern that the CEO could strategically choose where to live to avoid noncompete 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 *Noncompete Enforcement Index* to be positively related to *GAI* since the enforcement of noncompete 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 noncompete enforceability faced by the firm, while transfers between industries rise.[15]

There is also a distinction between the ex ante effects of noncompete agreements (human capital investment) and the ex post effects (labor mobility) as suggested by Posner et al. (2004). Therefore, we expect executives to have an ex ante incentive to accumulate more general skills in states with stronger enforcement of noncompete clauses. The idea is that if managers anticipate moving across industries, they might decide to invest more in general human capital rather than firm-specific knowledge to enable 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). In our setting, the exclusion restriction is likely to be satisfied 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 CEOs. Alternatively, we use the level of enforcement of noncompete agreements of the state of the first position over the CEO's career as an instrument for *GAI*. Going further back in time makes it more plausible that the exclusion restriction is not violated. However, we cannot completely rule out the possibility that an unobserved CEO time-varying characteristic, which is correlated both with current innovation and the *Noncompete Enforcement Index*, makes innovation linked to the instrument for reasons other than the generality of human capital.[16]

Table 8 shows the results of the instrumental variables estimation for *Patents* and *Citations*. The regressions include the same control variables as in Tables 3 and 4, as well as industry-year fixed effects and firm fixed effects. Panel A shows the results using the instrument based on all past positions, and panel B shows the

**Table 8.** Instrumental Variables

| | First stage | Second stage | |
|---|---|---|---|
| | *General Ability Index* | log(1 + *Patents*) | log(1 + *Citations*) |
| | (1) | (2) | (3) |
| Panel A: Instrument based on all past positions | | | |
| *General Ability Index* | | 1.070*** | 0.757** |
| | | (3.522) | (2.505) |
| *Noncompete Enforcement Index* | 0.080*** | | |
| | (5.100) | | |
| Controls | Yes | Yes | Yes |
| Industry-year fixed effects | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes |
| Number of observations | 6,419 | 6,419 | 6,419 |
| *F*-statistic of instrument | 26.02 | | |
| Panel B: Instrument based on first position | | | |
| *General Ability Index* | | 0.664*** | 0.658*** |
| | | (4.996) | (4.448) |
| *Noncompete Enforcement Index* | 0.110*** | | |
| | (10.200) | | |
| Controls | Yes | Yes | Yes |
| Industry-year fixed effects | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes |
| Number of observations | 6,524 | 6,524 | 6,524 |
| *F*-statistic of instrument | 104.04 | | |

*Notes.* This table presents estimates of instrumental variables methods using two-stage 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*). In panel A, *Noncompete Enforcement Index* is the average Garmaise (2009) noncompete agreement enforcement index at the state-year level across all positions the CEO has had in publicly traded firms. In panel B, *Noncompete Enforcement Index* is the Garmaise (2009) noncompete agreement enforcement index at the state-year level for the first position the CEO has had in publicly traded firms. The sample consists of ExecuComp firms for which the 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 period 1993–2003. 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 A.1 in the appendix. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses.

** and *** indicate significance at the 5% and 1% levels, respectively.

results using the instrument based on the first position of the CEO's career.

Column (1) reports the first-stage regression estimates. As expected, we find that the *Noncompete Enforcement Index* is positively and significantly correlated with *GAI*. The *F*-statistics of the first-stage regressions are 26 and 104 in panels A and B, respectively—well above the conventional threshold for weak instruments. The first-stage results indicate that *GAI* increases by 0.16–0.22 when the *Noncompete Enforcement Index* changes by 2, which corresponds to a one-standard-deviation shock. 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 and significant. The second-stage results show that a 0.16 increase in *GAI* (obtained from the first stage in panel A) leads to a 17% increase in *Patents* and a 12% increase in *Citations*. The economic effect on *Patents* and *Citations* of a change in *GAI* driven by a one-standard-deviation change in the *Noncompete Enforcement Index* is similar to the one estimated previously using the OLS and fixed-effects regressions.[17]

Overall, the effects of *GAI* on innovation using instrumental variables methods are similar to those in our main tests, suggesting that the positive impact of general managerial skills on innovation is robust to endogeneity concerns. The results support our hypothesis that the general ability of CEOs affects innovation output. We find that making the human capital of a CEO more general generates an increase in both the number of filed patents and the citations of those patents.

### 5.2. Innovation Productivity and Firm Valuation

To investigate whether innovation produced by generalists adds to firm valuation, 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-day 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 patents) and specialist CEOs (71,386 parents).

Table 9 shows the results. We find that mean and median *CAR* are positive and significant in the sample of generalist CEOs, which is consistent with the notion that innovation by generalists adds to firm valuation. 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 et al. (2017). The mean and median *CAR* for specialists are significantly lower than those for generalists. The difference in means is six basis points per patent using market-adjusted returns and eight basis points using the market model. These results also help to rule out the concern that generalists are matched to nonpracticing entities, commonly designated by "patent trolls." Cohen et al. (2016) show that the patents nonpracticing entities assert are, on average, of lower quality than those asserted by practicing entities.[18]

We also run regressions (untabulated) using Tobin's *Q* as the dependent variable and *GAI* as the

**Table 9.** Patent Grant Announcement Abnormal Returns and General Managerial Ability

| | Market-adjusted returns | | Market model | | Number of observations |
|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | |
| *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 | |

*Notes.* This table shows mean and median *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-day estimation window $(-270, -11)$. The sample consists of ExecuComp firms for which the 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. The *p*-values of test of difference in means and Pearson chi-square of test of difference in medians are reported at the bottom of the table; *t*-statistics and Wilcoxon signed-rank test statistics are reported in parentheses.

main explanatory variable. The *GAI* coefficient is positive but statistically insignificant, which is consistent with Custódio et al. (2013). This insignificant relation between *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 firm valuation. If there is an optimal matching based on CEO type (generalist versus specialist) and innovation policy, we will not observe cross-sectional differences in firm valuation based on CEO type. In other words, if we replaced a "well-matched" generalist with a specialist CEO, only then would we observe a reduction in firm valuation.

Overall, the results support the view that innovation adds to firm valuation. 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.

### 5.3. Robustness Checks

Results of several robustness checks of our primary findings are presented in the Internet appendix. These robustness checks support the idea that generalist CEOs improve the quantity and quality of innovation. We discuss them briefly here.

We first use the ratio of R&D expenditures to assets (an input-oriented measure of innovation), stock return volatility, and total factor productivity as alternative measures of innovation and its productivity. We also perform robustness checks related to the construction of *GAI*. We use a dummy variable that takes a value of 1 for generalist CEOs or estimate separate regressions for each individual component of *GAI*.

Next, we run robustness checks of our instrument variable estimator. We control for the past experience of the CEO in innovative firms as generalist CEOs are more likely to have worked in innovative industries in the past. We use alternative definitions of the noncompete enforcement index in which the index is based on the current firm location (as opposed to the employment history of the CEO). We interact the index with the level of in-state competition following the specification in Garmaise (2009).

We further control for R&D expenditures and additional firm and CEO observable characteristics, which include market and accounting; performance; firm age; institutional ownership; corporate governance; and CEO tenure, age, education, compensation, overconfidence, and network. We also run our main tests using alternative methods, which include propensity score matching, and negative binomial and Poisson regressions for patent and citation counts.

Finally, we perform a set of robustness checks to our sample definition. We drop IBM as a potential outlier or firms with zero patent or citation counts. We consider a subsample of noninnovative industries and different tenure cutoffs. In these subsamples, the CEO is less likely to have been hired with the goal of increasing innovation; therefore, selection concerns are mitigated.

## 6. Conclusion

Our analysis of whether CEO general managerial skills matter for innovation finds that CEOs who gain more general 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 research activities. We provide evidence consistent with a link from the generality of CEO human capital to the willingness to innovate and take risks using an instrument for general skills based on the variation in the enforceability of noncompete agreements across states and over time.

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 in addition to internal mechanisms such as executive compensation plans. Furthermore, generalist CEOs extend the firm's boundaries and bring more diverse knowledge to the firm because they have been exposed to different industries, firms, and roles. 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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## Appendix

**Table A.1.** 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 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, defined as patents filed by the target firm in the previous five years prior to the event (NBER patent database). |
| *Technological Proximity* | Technological proximity between the patents filed in year $t$ and the patents filed by another firm in which the CEO has a board seat during his tenure at these firms: $$P_{ijt} = \sum_{k=1}^{K} f_{ikt} f_{jkt} \bigg/ \left( \sum_{k=1}^{K} f_{ikt}^2 \cdot \sum_{k=1}^{K} f_{jkt}^2 \right)^{1/2},$$ where $f_{ikt}$ is the fraction of firms $i$'s patents that belong to patent class $k$ at time $t$, and $f_{jkt}$ is the fraction of patents filed by the firm in which the CEO has a contemporaneous board seat that belong to patent class $k$. |
| | 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). |
| *Noncompete Enforcement Index* | Average noncompete agreement enforcement index (Garmaise 2009) at the state-year level across all positions the CEO has had in publicly traded firms or, in alternative, the index of the state and year of the first position of the CEO's career. |
| | Panel C: Firm characteristics |
| *Sales* | Sales in millions of dollars (Compustat SALE). |
| *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 (Compustat PPENT/AT). |
| *CAPEX* | Capital expenditures divided by total assets (Compustat CAPX/AT). |
| *Leverage* | Total debt, defined as long-term debt plus debt in current liabilities, divided by total assets (Compustat (DLC + DLTT)/AT). |
| *Family Firm Dummy* | Dummy variable that takes a value of 1 if the firm is family owned and 0 otherwise (Anderson and Reeb 2003; http://www.ronandersonprofessionalpage.net/data-sets.html, accessed October 2015). |
| *Tight Labor Market Dummy* | Dummy variable that takes a value of 1 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 1 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 industry return (Fama–French 48 industry classification) over two different periods, 1993–1997 and 1998–2003, such that at least 24 nonmissing 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). |
| *Number of Firms MSA-Industry* | Number of other firms in the firm's industry (two-digit SIC code) that are also located in the firm's MSA (Compustat). |
| *Fraction MSA-Industry* | Fraction of all firms in the MSA that are in the firm's industry (two-digit SIC code) (Compustat). |

## Endnotes

[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, Frydman 2015). In addition, Lazear (2005) shows that students who have diverse work and educational backgrounds are more likely to become entrepreneurs.

[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.

[3] Jack Welch, General Electric's CEO, described this new organizational model in the 1990 annual report: "[GE] is a boundaryless company . . . where we knock down the walls that separate us from each other on the inside and from our key constituencies on the outside" (quoted in Hirschhorn and Gilmore 1992, p. 104).

[4] We also control for state- and industry-year fixed effects to account for state- and industry-specific events in a given year that could affect innovation. For instance, Chava et al. (2013) show that shocks to the local market power of banks have an impact on innovation. Mukherjee et al. (2015) show that increases in state-level corporate tax rates have a negative impact on innovation.

[5] Researchers have examined whether corporate outcomes are affected by CEO characteristics (Kaplan et al. 2012, Bertrand and Schoar 2003). Fee et al. (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.

[6] This approach addresses the criticism by Fee et al. (2013) that CEO turnover often coincides with a change in strategy such as investing more in innovation.

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

[8] Our results are robust to dropping IBM from the sample.

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

[10] In robustness tests, we show that estimates are similar when we use raw citation count and alternative methods to adjust for truncation bias.

[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 et al. 2013). Yonker (2017) shows that geography affects both labor supply and demand in the market for CEOs, and Bouwman (2013) shows that geography affects CEO compensation.

[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 (2014).

[14] Noncompete clauses are less frequent in nonexecutive position contracts. We obtain similar instrumental variable estimates (untabulated) when we calculate the *Noncompete Enforcement Index* excluding past nonexecutive positions.

[15] Marx et al. (2009) show that noncompete 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 noncompete enforcement policy as a natural experiment.

[16] Another concern with the instrument is the validity of the exclusion restriction because of location decisions of the CEO. A manager with general managerial ability might self-select to move to a state with higher enforceability of noncompete agreements, because if the match does not work out, he can more easily move compared to a specialist. This concern is mitigated by using the enforceability of noncompete agreements in the state of the CEO's first position as an instrument and the fact that the *Noncompete Enforcement Index* is time varying within states.

[17] The instrumental variables estimates are larger than those of the OLS as *GAI* measures general human capital with error, and therefore, OLS are biased toward zero as a result of attenuation bias.

[18] The higher stock market reaction to patents filed by generalist CEOs may have an alternative explanation. The reaction may not reflect that patents filed by generalist have higher value than those filed by specialists but simply a larger surprise effect. When specialists innovate, the reaction is low because the stock price already incorporates this effect as there is a small surprise effect. When generalists innovate, the reaction is high as there is a large surprise effect.

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