R&D MANAGEMENT

How top management team social status impacts innovation

Ali Radfard[1,*], Luca Pistilli[2] and Alessia Paccagnini[2]

[1]Aston Business School, 295 Express Way, Birmingham, B4 7ER, UK. a.radfard@aston.ac.uk
[2]Lochlann Quinn School of Business, University College Dublin, Belfield, Dublin 4, Ireland, luca.pistilli@ucd.ie; alessia.paccagnini@ucd.ie

Scholars have investigated the effect that top management team (TMT) status has on several organizational dimensions, including strategic decision, risk propensity, and, ultimately, performance. However, the existing literature is relatively silent on the effect of TMT status on innovation. Our scope is to cover that research gap. Grounding our reasoning on two different yet intertwined literature streams – one on the TMT status and the other on innovation – we predict that TMT status should be positively correlated with innovation and its market value, but not with its scientific value. Relying on a unique, hand-crafted dataset composed of 833 firm-years' observations for the period 2005–2010, we can validate our hypotheses. Our study contributes to a better understanding of the relationship between TMT status and innovation generated by the respective firm. Finally, the study discusses limitations and recommendations for further research.

1. Introduction

Innovation, like almost any other firm activity, includes a social dimension: This concept is grounded in the idea that economic relations co-exist with social attributes (Polanyi and MacIver, 1944; Granovetter, 1985; Allen and Katz, 1992; Moehrle et al., 2005). In essence, knowledge, which is a key precursor for innovation, is generated through interaction between organizational actors within and across organizations (Schumpeter and Nichol, 1934; Nelson and Winter, 1982; Uzzi, 1996; Guan and Liu, 2016). Therefore, the innovation process is affected by the social attributes of organizational members. Prior research has extensively addressed this aspect of knowledge generation in general, and innovation more specifically, considering how and the extent to which inventors detain intra-organizational and inter-organizational ties (Gulati, 1998; Guan and Liu, 2016). In particular, the degree of connection of inventors with other individuals, such as academic scientist networks, affects a firm's innovation (Welsh et al., 2008; Libaers, 2017). In a similar vein, the connectedness of users (Schweisfurth and Herstatt, 2016) and suppliers (Tomlinson and Fai, 2016) also plays a role in determining the overall level of a focal firm's innovativeness.

Yet, it is surprising that much less attention has been paid to the role of social dimension in top management teams (henceforth TMT) in a firm's innovation (Talke et al., 2010), even if some studies suggest that, for example, TMT heterogeneity may influence exploratory innovation (Alexiev et al., 2010) and TMT political capital can impact innovation in general (Xia and Liu, 2022). Where scholars have focused on the general TMT role in promoting innovation, they have primarily concentrated on TMT demographic and knowledge diversity (e.g., Chung et al., 2018; Boone et al., 2019; Belderbos et al., 2020), TMT research and industry orientation (e.g., Daellenbach et al., 1999; Van de Wal et al., 2020), and other TMT dispositional characteristics (e.g., Liu et al., 2012; Ahn et al., 2017). This paucity of research on the effect of the social dimension of TMT on firms' innovation is problematic, especially when viewed from an upper-echelons theory perspective, which posits that TMT situational attributes largely impact firm decisions and outcomes (Hambrick and Mason, 1984; Hambrick, 2007). Hence, the existing literature fails to fully consider how TMT situational attributes, which influence core strategic decisions within the focal firm (Cao et al., 2015), could help to explain why firms are heterogeneous from an innovation perspective (Ahuja and Morris Lampert, 2001). We aim to shed additional light on the aforementioned issue.

We address this issue in the present paper by focusing on the effect of TMT social status – a key element of social dimension (Piazza and Castellucci, 2014) – on the patenting outcomes of firms as a proxy for innovation. Social status is understood as a key social dimension and can be broadly defined as the inter-subjective social respect, rank, and recognition bestowed upon individuals by others (Washington and Zajac, 2005). Drawing from research on TMT social status (e.g., Hambrick, 2007; Piazza and Castellucci, 2014) and innovation (e.g., Autio et al., 2000; Berry, 2014), we argue that high-status TMT brings in more resources and creates more opportunities to generate innovation within a firm, as social status brings privileged access to resources and opportunities to its holders (e.g., Kim and Oh, 2002; Lüthje and Franke, 2003), which are ultimately crucial for promoting innovation. However, given that status pertains to a social (and therefore, subjective) dimension, this effect should be asymmetric for social appeal and the objective value of innovation. We propose, in this paper, a framework that helps to demonstrate whether and how the social status of TMT affects innovation. More precisely, we propose that the social status of a firm's TMT has a positive effect on a firm's innovation, operationalized as the number of patents. Moreover, the social status of TMT is expected to have a positive effect on the market value (as a subjective dimension) of the firm's patents but should not be associated with their scientific value (as an objective dimension). We find support for our hypotheses using a hand-crafted dataset of 833 firm-years' observations for the time window 2005–2010 (extended to 2014 in a robustness test).

We contribute to two broad literature streams, namely, innovation and TMT social status. Our first contribution consists in clarifying that high-status TMTs are expected to be associated with more innovation, as high status conveys more resources being allocated to R&D activities (e.g., Sievinen et al., 2020), and the same status tends to be connected with a higher-risk propensity of the TMT (e.g., Ling et al., 2008; Rovelli et al., 2020). These combined elements are expected to increase R&D investments and, in turn, innovation. Second, our study unveils that TMT social status is expected to enhance the market value innovation, while having almost no effect on the scientific value of these patents. As such, we provide evidence that some TMT characteristics can also influence the quality of innovation. Specifically, our study shows how TMT situational attributes can impact innovation quality (e.g., Ahn et al., 2017; Chung et al., 2018; Boone et al., 2019; Belderbos et al., 2020), as well as showing what happens with dispositional attributes (e.g., Nadkarni and Chen, 2014; Cummings and Knott, 2018). Finally, we add to the broader academic debate on the role of social status within organizations (e.g., Piazza and Castellucci, 2014; Anderson et al., 2015; Mahadevan et al., 2019), showing that within the innovation context, TMT social status is associated with higher subjective quality, but has no effect on the objective quality of innovation.

2. Theory and hypotheses

We ground our theoretical argumentation into two different yet intertwined literature streams: the first on TMT social status and the second on innovation. Since we simultaneously rely on the aforementioned literature streams to develop our two core hypotheses, we structure this section in line with the established hypotheses-conceiving process. First, we elaborate on the general concept of TMT status; second, we link that literature stream with the stream on innovation; third, we clarify the claimed relationship between TMT social status and focal firm's innovation; and fourth, we assess how the same TMT social status influences both the scientific and market (or economic) value of the innovation.

2.1. *TMT social status*

Existing literature defines TMT social status as the influence and reputation attributed to TMT members by colleagues working for the same organization, social external networks, and third-party evaluation (Perretti and Negro, 2006; Magee and Galinsky, 2008). Thus, the status attributed to individuals belonging to the same TMT determines the overall status of TMT itself (e.g., Bunderson and Reagans, 2011; Liu et al., 2012; Piazza and Castellucci, 2014). There is a large consensus among scholars of different disciplines that TMT social status can affect several organizational dimensions (e.g., Washington and Zajac, 2005; Tang et al., 2016). Hambrick and Mason (1984) opened this research avenue, which investigates how the characteristics and peculiarities of TMT can somewhat predict the strategic decisions and directions undertaken by the firm they lead. The driving principle is that senior managers have the right power to influence strategic decisions and, ultimately, the performance of the firm. Their status plays a key role in this regard (Bromiley and Rau, 2016).

The existing literature builds on the concept that TMT social status can be an antecedent for firms' innovative performances in established organizations, as well as in small entrepreneurial firms and startups (Daellenbach et al., 1999). The key tenet is that TMTs characterized by a higher degree of status feel more confident in undertaking "aggressive" strategic directions, such as heavily investing in risky activities like R&D (Ling et al., 2008). In fact, R&D is by definition a risky endeavor that sees no certain return (Bromiley et al., 2017), and while the expected value of R&D projects can be esteemed ex-ante, the predicted outcome may often be achieved only in the long run (Conti, 2014). This higher propensity for risk-taking in relation to high-status top executives seems to be largely determined by the overconfidence that high-status leaders tend to have in themselves (Tang et al., 2016). While scholars have predicted mixed results regarding how TMT overconfidence impacts performance (Clark and Maggitti, 2012), there is a considerable consensus that the same overconfidence is expected to lead to greater engagement in riskier activities, such as innovation (Tang et al., 2016). In particular, recent studies highlight that attaining elevated status through exceptional performance mitigates deviant risk-taking behaviors like bribery, while concurrently fostering aspirational risk-taking endeavors such as R&D (Xu et al., 2019).

2.2. Innovation

Innovation process is a fundamental activity for innovative enterprises and plays an essential role both in the short-run profitability and the long-run sustainability of the firm (e.g., Autio et al., 2000; Song et al., 2006; Berry, 2014; Schulze et al., 2015). Innovation can be generated by relying both on internal sources, such as R&D labs, and external sources, such as the lead user, where crowdsourcing and pyramiding searching processes can be implemented (Urban and Von Hippel, 1988; Von Hippel et al., 2009). Our focus is on the innovation generated within the boundaries of the focal organization, namely, through R&D activities (Howells et al., 2003; De Mattos et al., 2013; Chappin et al., 2019).

However, there are different ways of disentangling and classifying the innovation generated by a firm, for example, by depending on whether or not it is codifiable (e.g., Haas and Hansen, 2007). In this paper, we are mostly interested in assessing the quality, that is, the rigor, soundness, and insight of the innovation conveyed (Kane et al., 2005). Assessing the quality of innovation deployed through firms' R&D activities is a non-obvious task (e.g., Rynes et al., 2001; Lahiri, 2010; Shang et al., 2017). One possible way of measuring the quality of innovation is to look at its scientific and market value (Capaldo et al., 2017; Smart et al., 2019), where the market value depends on the financial returns that an organization can achieve through its commercialization and the scientific value is represented by how much additional innovation has been developed based on the former (Capaldo et al., 2017). Existing literature shows that the scientific value of innovation is influenced by several external conditions, such as the institutional environment where the focal firm operates (Mueller et al., 2013), the innovative endeavors of its competitors (Katila and Chen, 2008), or the geographic position of inventors (Audretsch and Feldman, 1996). Scholars also highlight how organizational peculiarities can influence the scientific quality of innovation, including the firm's absorptive capacity (Cohen and Levinthal, 1990), its combinative capacity (Kogut and Zander, 1992), and the comportment of R&D workers (Felin and Hesterly, 2007).

The market or economic value of innovation generated is similarly expected to be affected by industry and firm-specific features (Nesta and Saviotti, 2006; Hussinger and Pacher, 2019). Surprisingly, though, the existing literature provides little evidence about how TMT characteristics may affect the quality of innovation, both from a scientific and market value perspective. In particular, while scholars show that the TMT status of a given firm is expected to impact several organizational dimensions, we know little about how such a status can affect innovation and its quality (i.e., its scientific and market values). Our study aims to reach a better understanding of this issue. Thus, we ask: *How is TMT status expected to affect firstly innovation within the focal firm, and secondly its related market and scientific values?*

2.3. TMT social status and innovation

A firm's general performance is influenced by TMT attributes, whether dispositional and fixed or situational in nature (e.g., Hambrick and Mason, 1984;

Hambrick, 2007). Existing research shows support for this connotation from different angles and perspectives (e.g., Medcof, 2008; Minichilli et al., 2010; Richard et al., 2019).

For instance, scholars have unveiled how social status brings privileged access to resources and opportunities to its holders (e.g., Kim and Oh, 2002; Lüthje and Franke, 2003). Thus, we expect a firm's innovation (operationalized as patenting to reflect this superior access, as high-status TMT can influence a firm's innovation through more accurate strategic leadership (O'Reilly et al., 2014), superior support (Nadkarni and Chen, 2014), and high-quality new hirings (Elenkov and Manev, 2005). Hence, it is reasonable to anticipate that a firm's capacity for innovation, as manifested by its patenting outcome,[1] will serve as an indicative gauge of its advantageous access to resources and networks. This conjecture finds grounding in the fact that high-status TMT possess the potential to exert a significant impact on a firm's innovation trajectory through a range of mechanisms. Specifically, the influential role of high-status TMTs in shaping innovation outcomes can be attributed to their capacity to furnish more accurate and informed strategic guidance, derived from their extensive experience and well-established industry connections (O'Reilly et al., 2014). Moreover, the elevated status of the TMT can translate into superior support systems that enable efficient resource allocation, thereby fostering an environment conducive to innovative endeavors (Nadkarni and Chen, 2014). Furthermore, the prominence of a firm's TMT can also translate into an enhanced ability to attract and onboard individuals possessing cutting-edge knowledge and skills, which can contribute significantly to the innovation process (Elenkov and Manev, 2005). In this regard, it is rational to predict a positive effect of TMT status on a firm's level of innovativeness, as researchers have found, on average, a positive impact of investments in R&D on innovation, where the latter can be measured as the intensity of patenting activities of the focal firm (Song et al., 2006; Grigoriou and Rothaermel, 2017). In sum, we argue that this effect of TMT status on innovation comes about through both resource and opportunity channels. The resource channel implies that TMTs play an active resource role in promoting change and innovation, as well as in facing a disruption by aligning the new capabilities required with the traditionally detained ones (Sievinen et al., 2020). In other words, higher-status TMTs are expected to have a greater capacity to convey resources for R&D, which are essential for promoting innovation. Regarding the opportunity channel, existing literature recognizes that high-status TMTs are expected to have a positive impact on the realization of innovation opportunities (Rovelli et al., 2020), due largely to the higher-risk propensity of the same high-status TMT (Ling et al., 2008). In fact, investing in R&D embeds a certain degree of risk, as the innovation outcome is not guaranteed ex-ante, and can only be esteemed in probabilistic terms (Conti, 2014; Bromiley et al., 2017). Consequently, decision-makers with higher-risk propensity are expected to invest more in risky activities, such as R&D. Existing literature clarifies that high-status TMTs, due to their general higher self-confidence (Tang et al., 2016), are also expected to be less reluctant to undertake risky activities, as they are, indeed, more risk-prone (Ling et al., 2008). Since there is considerable consensus on the positive implications of R&D investments on innovation outcomes (Daellenbach et al., 1999; McCarthy and Gordon, 2011), we argue that greater risk propensity should also lead to superior innovation outcomes. Hence, higher TMT status should imply more resources for R&D and a higher-risk propensity. These two elements combined are expected to promote innovation:

Hypothesis 1 Higher TMT social status is expected to increase the innovativeness level of the focal firm.

2.4. *TMT social status and market/scientific value of innovation*

As status is an inter-subjective social construction based on social agreement (Washington and Zajac, 2005), we must consider it as a social dimension (Lenski, 1954). It is well documented that status does not necessarily reflect the underlying skills and capabilities of an individual (Piazza and Castellucci, 2014). Conversely, referring to innovation, the existing literature also illustrates that the related market values may not necessarily correspond to their scientific value (e.g., Bozeman and Rogers, 2002; Denicolai et al., 2014; Arora et al., 2018). More specifically, highly valuable innovation from a scientific point of view may not be fully appreciated by the market (often in the form of a product/service that embeds the innovation), and very successful innovation from a commercialization perspective might be judged as trivial in scientific terms. The existing literature defines the market value of innovation as the financial returns that a firm can derive from its commercialization, while its scientific value is determined by the same innovation's capacity to impact subsequent innovations (Capaldo et al., 2017). We elaborate on this distinction and expect it to manifest in the attributes of firm patents, as a signal of the innovation developed. In particular, we believe that high-status TMTs bring market appeal with them. This is because high status resonates with mass admiration, acceptance, and desirability (Anderson et al., 2015; Mahadevan et al., 2019). In addition, considering the aforementioned resource channel, it is reasonable that the superior capacity of high-status TMTs in attracting resources will positively affect not only R&D but also other organizational functions, such as marketing and sales. Consequently, superior resources (both monetary and non-monetary) available for marketing and sales are generally expected to enhance the innovation/product appeal and evaluation from a customer's point of view (Rosenberg and Czepiel, 1984). In essence, we argue that while the capacity (that high-status TMTs have) to attract superior resources positively impacts R&D, and hence increases a firm's innovation (Hypothesis 1), the same capacity positively affects marketing, with direct implications on how external actors perceive the same innovation as more valuable. In addition, the greater appeal and popularity of the TMT is also expected to support a more effective exposure and promotion of final products on the market (Dimov et al., 2007), which ultimately tends to better perform in terms of sales, diffusion, and profitability (Pollock et al., 2010). These considerations combined lead us to believe that greater TMT status should lead, on average, to a higher market value of innovation generated by the firm:

Hypothesis 2 Higher TMT social status is expected to increase the market value of innovation generated by the focal firm.

While superior resources for marketing – deployed by high-status TMT through the resource channel, in combination with a greater capacity to expose and promote new products – are expected to elevate the market (or perceived) value of innovation, we cannot predict the same TMT status to leverage the objective quality of innovation, that is, its scientific value. In fact, among the organizational aspects that can impact innovation's scientific value, the existing literature includes absorptive capacity (Cohen and Levinthal, 1990), combinative capabilities, individual inventors' peculiarities and behavior (Felin and Hesterly, 2007), and knowledge maturity (Capaldo et al., 2017). These elements are not expected to be impacted by TMT (Liu et al., 2022). In fact, the scientific value of an innovation depends largely on the capabilities, skills, and competences of the inventors (Conti et al., 2014) – namely, the employees who are working for the R&D department – and the TMT status plays little role in this context. However, one may argue that a greater ability to attract resources of high-status TMTs (resource channel) may also grant access to "better" researchers on the job market.[2] While superior resources and status from an organizational perspective undoubtedly widen the possibilities for the same firm to attract more valuable employees (Bidwell et al., 2015), we argue that executives are indeed interested in maximizing the profitability of innovation, but not its scientific value, and those dimensions are not necessarily correlated (Geuna and Nesta, 2006). Hence, we expect resourceful executives to focus on hiring those researchers who tend to generate highly profitable innovation (Palomeras and Melero, 2010), with little or no consideration of how that innovation will be evaluated by other scientists. Indeed, traditional for-profit firms are expected to maximize performances (i.e., the market value of innovation, in our context), and not the overall impact that innovation may have on the scientific community (i.e., the scientific value of innovation). In other words, even if high-status TMTs could have the chance to increase the scientific value of innovation, they are unlikely to be interested in doing this, as their ultimate goal is to maximize profitability (Priem, 1990). Clearly, a different reasoning applies to non-profit organizations or research institutions (Hudon et al., 2020). Moreover, existing literature suggests that "star" scientists may be difficult to manage, as they can exert more influence and/or assume a central role in the firm (Kehoe and Tzabbar, 2015). Thus, high-status TMTs may not be willing to hire them to avoid potential conflicts and tensions.

As a final consideration, since the scientific value has more to do with the objective and inner (real) quality of innovation (Phene et al., 2006), we do not expect the TMT status to have any significant influence on it, as it depends mostly on innovators themselves. In fact, social status, as a socially constructed dimension (e.g., Washington and Zajac, 2005), is characterized by a non-objective inner nature and, hence, a degree of subjectivism determined by how it is evaluated or judged by third parties (Astley, 1985). In this regard, while a socially constructed dimension may influence the market evaluation, the same is not expected to affect an objective and non-socially constructed dimension, such as the scientific value of innovation. In sum, we formally predict:

Hypothesis 3 Higher TMT social status is not expected to affect the scientific value of innovation generated by the focal firm.

3. Methods

3.1. Context and sample

The main sample used for this paper is a panel dataset of S&P 1500 firms in manufacturing industries

(2-digit SICs from 20 to 40). S&P 1500 companies are established, widely traded, and employed in relevant prior research (e.g., Chang et al., 2019). This context enables us to assess TMTs' social status impact on the innovativeness of firms. In order to build our database, we tracked the public companies listed in S&P 1500 between 2005 and 2010. For this time window, we collected financial data, ownership, board, and patent data and merged it together from COMPUSTAT ANNUALS, BOARDEX, EXECUMP, CAPITAL IQ, RISK MATRICS, FACTIVA, LEXIS-NEXIS, SEC-EDGAR, WHO'S NEWS, Annual reports of companies, and Kogan's patent database (Kogan et al., 2017). The end date of our sample was due to the availability of Kogan's full patent data (up to 2010) at the time of collecting the present paper's data (Kogan et al., 2017). However, an extended dataset between 2005 and 2014 is used for robustness. The universal sample (obtained by dropping the firm-year observations with missing data) included 833 firm-year observations, as an unbalanced panel dataset over five years. We used Kolmogorov–Smirnoff's two-sample test to ensure that there was no significant difference between the main characteristics (such as size and sales) of the dropped firm-year observations and the universal sample's observations.

3.2. Dependent variables

3.2.1. Patent count

The first dependent variable we use to test Hypothesis 1 is the firm's innovativeness as measured by the number of patents granted to a firm in a specific year (Cohen and Levin, 1989; Arroyabe et al., 2020; Van de Wal et al., 2020). It is a common practice in prior research to focus on granted rather than all-filed patents because it is believed that granted patents that go through the review process show success (Ahuja and Katila, 2001). Nevertheless, to ensure the reliability of our findings, and to account for potential instances where patents generated and filed within our observation period are granted at a subsequent date, we undertake a robustness check where we substitute patents that are granted within our observation window with those that are applied for within the same timeframe but subsequently granted. In our baseline linear models, we employ the log of granted patents plus 1 (to avoid indeterminate numbers resulting from logging zero) (Ucar, 2018; Fich et al., 2023), at the end of each year, as using the gross number of patents in the linear models gives rise to the issue of overdispersion and inconsistent estimations (Keum, 2021). For benchmark Poisson specifications, we just use the raw patent count.

3.2.2. Market value of patents

We assess two dimensions of patents' quality to test Hypotheses 2 and 3, following Kogan et al. (2017). The first dimension is the market value of granted patents and the market value of granted patents for a firm in a given year is calculated by summing up the market value of all patents granted to a firm at the end of each year, where market value is the abnormal stock return following the news of a patent being granted within a three-day window. We use the natural logarithm of this number to avoid overdispersion. While it may be argued that a three-day window is a short time to measure the economic value of patents, it is a common practice to measure the market value of patents "at the issuance event of patents" (Kogan et al., 2017; Arora et al., 2022), as is the case with the market value of other firm events.

3.2.3. Scientific value of patents

The second dimension of patents' quality is the scientific value of granted patents (Kogan et al., 2017). This is calculated as the aggregation of the forward citations to all patents granted to a firm in a given year. The number of citations is obtained for each patent at the start of the grant year and continues until the end of 2010. It is further weighted by average citations to all patents granted in the same year as each calculated patent. We use the log of the aggregated citations; otherwise, overdispersion can occur. We track the forward citations up to 2020 as a robustness check.

3.3. Independent variables

3.3.1. Social status of TMTs

In prior corporate governance studies, the status of the corporate elite is measured in several ways. However, there are two dominant measurement approaches. First, researchers have used the number of outside directorships held by a focal director as a measure of status. This has been the most prevalent measure and somehow the strongest empirically (Westphal and Khanna, 2003; Westphal and Shani, 2016). Sitting on the boards of other firms both causes and conveys status. Being invited to sit on other firms' boards constitutes both recognition of, and deferral to, a focal director. Second, educational credentials have also been used to measure status (Westphal and Shani, 2016). It is a standard variable included in the BOARDEX dataset showing the number of qualifications each manager owns each year. Indeed, the qualifications of a director show that he/she may have high social status. Since both approaches have their own strengths and limitations (for example, a highly educated individual may also be characterized by low social status), we combine the two approaches. Namely, we measure the status of each board member, including the CEO, using a composite measure that includes the number of his/her outside directorships and educational credentials in a given year and as a linear sum. We then calculate the average social status of a focal firm's TMT, in a given year, by dividing the raw sum of the social status of board members by the size of that board. We use each dimension separately in our regressions as a robustness check. The independent variables are lagged one year with respect to the dependent variables.

3.4. Control variables

To rule out alternative explanations, we included control variables on three levels – namely, CEO, board, and firm. These control variables have been frequently used in relevant prior research (Daellenbach et al., 1999; Liu et al., 2012; Ahn et al., 2017; Van de Wal et al., 2020). We included CEO compensation and CEO ownership because prior research shows that managers' monetary incentives influence the patenting and innovation's attitude in firms (Dechow and Sloan, 1991; Benartzi and Thaler, 1999). We measured CEO compensation by the natural logarithm of compensation for a focal CEO. We also measured CEO ownership as the proportion of common shares owned by a focal CEO. We included the gender of CEO because previous studies have shown that gender influences CEO decisions regarding patenting and innovation (MacCrimmon and Wehrung, 1990; Chung et al., 2018). CEO gender is a dummy assuming a value equal to 1 if a focal CEO is female. CEO tenure is another important factor affecting a range of investment decisions through changing CEO horizons (Wu et al., 2005). We measured tenure as the number of years a CEO was in his position in a specific firm. Board-level factors are shown to affect corporate patenting and innovation (Chung et al., 2018; Boone et al., 2019; Belderbos et al., 2020). Acknowledging these effects, we included in the present paper CEO-chairman continuity, board independence, board gender composition, and board ownership as controls. CEO-chairman continuity is a dummy set to be 1 if a focal CEO is the chairman of his/her firm's board. Board independence is measured as the ratio of independent directors within a firm's board. We computed the board female proportion as the ratio of female board members. Board ownership is measured as the proportion of shares owned by a given board. At the firm level, we also included institutional ownership, R&D expenditure, firm size, firm growth, and return on assets (ROA) as controls. Institutional owners may affect a firm's inventive activities and patenting activity through activism (Rong et al., 2017). Institutional ownership is measured as the concentration of the ratio of shares owned by institutional investors. Firm size and growth can affect corporate patenting through changing cash flows at the disposal of managers (Valentini, 2012). Firm size is operationalized through the natural logarithm of sales.[3] Firm growth is the percentage change in the focal firm's sales relative to the prior year. Also, prior research has shown that the recent performance of firms influences corporate patenting attitude by adjusting the baseline risk for the firm (Demirkan and Demirkan, 2012). Thus, ROA is operationalized as the industry-adjusted ratio of net income over total assets. Finally, R&D expenditure is also an important determinant of firm patenting and innovation outcomes (Van de Wal et al., 2020). We included R&D expenditure as the natural logarithm of firm investment in research and development activities. We included year, firm, and industry dummies in all models accordingly.

3.5. Analysis

Ideally, we should have been able to allocate high versus low status randomly to two groups of TMTs and observe how this changed their patenting. Yet, this ideal condition is far from reality, as TMT attributes are path-dependent and idiosyncratic. Hence, for explorative purposes, we employ linear panel regression analysis. This involves logarithmically transforming dependent variables and integrating both random and fixed effects (Wooldridge, 2010; Van de Wal et al., 2020). Results are presented in Table 3. However, as log-transformed linear specification may be problematic for analyzing patent count models (Cohn et al., 2022), we use count data models with Poisson robust clustered standard errors, panel random-effects, and panel fixed-effects modes as our benchmark specification (results reported in Table 4). Incorporating fixed effects into analyses involving patent count data can pose certain complexities. Therefore, in order to complement the implementation of fixed effects in Poisson or negative binomial count models (Hilbe, 2011), and following prior research (Blundell et al., 2002; Boone et al., 2019; Runge et al., 2022), we also employed a pre-sample mean estimator that is based on pre-sample means to account for unobserved heterogeneity[4] (Blundell et al., 1995; Bloom et al., 2013; Boone et al., 2019; Li et al., 2019). Prior research shows that this pseudo-fixed-effect method is superior and most suitable for implementing fixed effects in analyzing patent data (Blundell et al., 2002; Bettis et al., 2014). In order to test Hypotheses 2 and 3, we had to consider the fact that both patent attributes, that is, market value and scientific value, are logically determined at the same time. This means that the overall intrinsic value of patents (with scientific and market dimensions being part of this broader intrinsic value) is generated at the time of patent creation. As there are error correlations within the equations estimating the market and scientific value of patents, a system of simultaneous equations should be used to obtain consistent and efficient estimates (Greene, 2003). In order to analyze the relationship between TMT social status and the market value and scientific value of patents provided that the determinants of these two dependent variables are the same and there are repeated observations on the same sample members, we used seemingly unrelated regressions (SUR). SUR is a flexible random-effect model that satisfies the needs created by mentioned factors (Fiebig, 2001) (results reported in Table 6). We included year dummies in the seemingly unrelated regression models and did the robustness analyses with different specifications to investigate Hypotheses 2 and 3.

4. Results

Tables 1 and 2 show summary statistics and correlations for all variables. In order to investigate potential multicollinearity problems, we undertook variance inflation factor (VIF) tests (Flickinger et al., 2016). All VIFs report values below the threshold of 10; thus, we can confidently claim that multi-collinearity is not a problematic issue in the present study (e.g., see Kalnins, 2018).

The first set of results is related to testing Hypothesis 1. Tables 3 and 4 display the results predicting patent count relying on linear (Table 3) and Poisson count data models (Table 4).

Model 1 in Table 3 shows the effects of control variables for linear specification. It essentially captures the portion of patenting obtained in prior research (Boone et al., 2019; Arroyabe et al., 2020; Van de Wal et al., 2020). For instance, in line with prior research, it is observed that although an increase in a firm size increases patent count, tenure is not a significant predictor of patenting. Also, R&D expenditure is positively associated with the patent count, which is coherent from a logical viewpoint. Next, we include the main explanatory variable, the average social status of TMT. Consistent with Hypothesis 1, as the average social status of TMT increases, the patent count of firms also increases. Model 2 in Table 3 shows this evidence for linear specification with random effects (0.11; $p<0.05$).

As shown by Cohn et al. (2022), the log transformation plus 1 is not directly interpretable as semi-elasticity, but it is only a (poor) approximation of this one.[5] If we assume the existence of the approximation, we can provide an economic interpretation in the case of semi-elasticities. With our data, an increase of one standard deviation of the average social status of TMT, *ceteris paribus*, implies an average impact on the patent count of 2.69%.

Table 1. Summary statistics

Variable	Obs	Mean	SD	Min	Max
Patent count	833	3.217934	1.700015	0.6931472	8.527738
Patent market value	833	0.1705219	0.2062965	0.0019982	2.077199
Patent scientific value	833	0.0204901	0.0377381	0.0000102	0.467748
R&D spending	833	4.873786	1.901335	−1.877317	9.304832
CEO salary	833	6.876307	0.4632191	0	8.384093
CEO ownership	833	0.0099233	0.0240914	0	0.3996965
CEO tenure	833	6.040816	5.644583	0	56
CEO gender	833	0.0216086	0.1454892	0	1
CEO_chairman continuity	833	0.6410564	0.4799788	0	1
Board independence	833	0.9070866	0.1148447	0.3	1
Board female proportion	833	0.1542437	0.0942398	0	0.4444444
Board ownership	833	0.0223791	0.0748972	0.000021	0.9623013
Firm size change	833	6.00295	17.65198	−59.49	157.051
Institutional ownership	833	0.0400431	0.0194661	0.0137716	0.2057912
Firm size	833	8.724356	1.518772	4.238185	12.96001
ROA	833	−0.1563307	7.506762	−64.505	22.583
TMT's average social status	833	4.472024	0.786898	2.363636	8.909091

Table 2. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
R&D spending	1													
CEO salary	0.3931	1												
CEO ownership	−0.212	−0.158	1											
CEO tenure	−0.1418	−0.0458	0.6429	1										
CEO gender	−0.0047	0.0888	−0.036	−0.0128	1									
CEO-chairman continuity	0.1352	0.2629	0.0539	0.1926	0.1112	1								
Board independence	0.0783	0.1574	−0.1466	−0.1085	−0.0283	0.2252	1							
Board female proportion	0.2984	0.2641	−0.1876	−0.1458	0.1518	0.23	0.1177	1						
Board ownership	−0.2177	−0.0433	0.0201	0.0022	−0.0364	−0.2557	−0.3281	−0.042	1					
Firm size change	0.0543	−0.0032	0.0292	0.0185	−0.0134	−0.0498	−0.094	−0.0331	0.0211	1				
Institutional ownership	−0.2229	−0.2043	0.1282	0.1105	0.0967	−0.1422	−0.1077	−0.1275	−0.0207	−0.1027	1			
Firm size	0.5587	0.5724	−0.294	−0.1595	0.0867	0.2597	0.0511	0.3946	0.0411	0.0299	−0.2616	1		
ROA	0.0821	0.0932	−0.0607	−0.0766	−0.023	0.0609	0.0226	0.1135	−0.0294	0.1895	−0.225	0.1207	1	
TMT's average social status	0.4108	0.2897	−0.2051	−0.1283	0.2153	0.1737	0.1656	0.2255	−0.1182	−0.0124	−0.1098	0.3935	0.0491	1

All coefficients larger than |0.06| are significant at $p<0.10$ level.

In light of the mathematical issues discussed by Cohn et al. (2022), in particular, to have an appropriate economic interpretation, we test Hypothesis 1 by estimating Poisson specifications.

Model 1 in Table 4 documents the effects of control variables for panel Poisson specification with the random effect. Model 2 in Table 4 presents the effect of the average social status of TMT under panel Poisson specification with the random effect ($b=0.06$; $p<0.05$). To understand the economic interpretation of an increase of one standard deviation of a regressor in a Poisson model, we can apply the following mathematical formula:

$$e^{\beta * SD} = e^{0.06*0.787} = 1.0484.$$

This means that each additional increase of the standard deviation of the average social status of TMT is associated with an increase in the patent count by a factor of 1.0484, *ceteris paribus*. Alternatively, we can quantify an increase of 4.84% in the patents due to an increase of one standard deviation of the average social status of TMT.

Additionally, Model 3 in Table 4 ($b=0.05$; $p<0.01$) documents results with robust standard errors and industry dummies for Poisson specification, with an increase in the patent count of 4.013% for an increase of one standard deviation in the average social status of TMT, *ceteris paribus*. Robust standard error implementation allows us to reduce the heteroskedasticity issues in residuals. Industry dummies were used as it could be argued that mixed industries are inappropriate for patent data due to patenting heterogeneity across industries, and we investigated the industry effect in the linear panel model as well, by employing industry dummies in Model 3 of Table 3 ($b=0.1$; $p<0.05$), with an increase of 8.112% in the patent count for an increase of one standard deviation in the average of the social status of TMT, *ceteris paribus*.

To investigate the results under fixed-effects implementation, Model 4 in Table 3 and Models 4 and 5 in Table 4 are presented. Model 4 in Table 4 displays the results of the Poisson pseudo-fixed-effects estimation. In this case, the estimated coefficient for the average social status of TMT is positive and significant ($b=0.03$; $p<0.05$), with an increase of 2.389% in the patent count for an increase of one standard deviation in the average of the social status of TMT, *ceteris paribus*. Model 5 that shows Poisson fixed effects is consistent with Model 4 ($b=0.08$; $p<0.01$), with an increase of 6.50% in the patent count for an increase of one standard deviation in the average of the social status of TMT, *ceteris paribus*.

Therefore, the support for Hypothesis 1 is robust to the inclusion of firm fixed effects. Also, Model 4

Table 3. Results from linear panel regressions for predicting patent count

	(1)	(2)	(3)	(4)
	Linear random-effect patent count	Linear random-effect patent count	Linear random-effect patent count	Linear fixed-effect patent count
R&D spending	0.37***	0.36***	0.21***	−0.24***
	(8.15)	(7.91)	(3.42)	(−2.91)
CEO salary	0.04	0.04	0.02	0.03
	(0.78)	(0.73)	(0.41)	(0.64)
CEO ownership	−0.67	−0.47	−0.78	−1.25
	(−0.32)	(−0.23)	(−0.38)	(−0.51)
CEO tenure	0.006	0.005	0.006	0.01**
	(0.93)	(0.92)	(1.02)	(2.16)
CEO gender (c)	0.12	0.02	0.08	0
	(0.21)	(0.04)	(0.13)	
CEO-chairman continuity	0.14***	0.14***	0.14***	0.07
	(2.67)	(2.72)	(2.70)	(1.33)
Board independence	−0.92***	−0.88***	−0.92***	−0.33
	(−4.13)	(−3.93)	(−4.15)	(−1.41)
Board female proportion	−0.64*	−0.73*	−0.60	−0.65*
	(−1.70)	(−1.93)	(−1.58)	(−1.72)
Board ownership	−0.58	−0.56	−0.50	−0.23
	(−1.36)	(−1.30)	(−1.14)	(−0.56)
Firm size change	−0.003***	−0.003***	−0.004***	−0.005***
	(−3.74)	(−3.84)	(−4.28)	(−4.53)
Institutional ownership	−0.69	0.59	1.03	−0.15
	(−0.39)	(0.34)	(0.59)	(−0.09)
Firm size	0.18***	0.18***	0.41***	0.58***
	(3.06)	(2.95)	(4.86)	(4.73)
ROA	0.002	0.002	0.002	−0.00
	(0.89)	(0.84)	(0.74)	(−0.20)
TMT's average social status	–	0.11**	0.10**	0.22**
		(2.11)	(2.08)	(2.00)
N	833	833	833	806
R^2	51.40	52.14	–	11.8
Wald-χ^2	–	–	275.51	–

This variable is dropped from linear fixed-effect regression as it remains time-invariant in our sample within the window of our analysis; *z* statistics in parentheses.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

in Table 3, which is a linear specification with fixed effects, shows a positive and significant ($b=0.22$; $p<0.05$) coefficient for the average social status of TMT, assuming the existence of the semi-elasticity, an increase of one standard deviation of the average social status of TMT, *ceteris paribus*, implies an average impact on the patent count of 5.38%.

This latter linear fixed-effects model is only added for the sake of completeness because as discussed in the section on analysis, such specification can be problematic. Therefore, our models support the claim that the social status of TMTs has a positive impact on innovation for the focal firm.

Finally, Model 1 in Table 5 shows how these results are statistically significant when we extend the sample to include observations from 2005 to 2014.

In order to test Hypotheses 2 and 3, we carried out a seemingly unrelated regression.[6] Table 6 shows the results of this regression. Model 1 in Table 6 includes control variables for the market value of patents' estimation. In Model 2 of Table 6, the dependent variable is the market value of granted patents. The coefficient on the average status of TMT is positive and significant ($b=0.01$; $p<0.05$), with an increase of 0.783% in the patent count for each additional increment of one standard deviation of the average of the social status of TMT, *ceteris paribus*.

Model 3 in Table 6 includes control variables for the scientific value of patents' estimation. In Model 4 of Table 6, having the scientific value of granted patents as a dependent variable, the coefficient on the average status of TMT is negative but insignificant

Table 4. Results from panel, robust, and fixed-effect Poisson for predicting patent count

Variables	(1) Poisson panel random effects	(2) Poisson panel random effects	(3) Poisson robust	(4) Poisson pseudo-fixed effects (using PSM)	(5) Poisson fixed effects
R&D spending	0.21***	0.20***	0.19***	0.2***	0.06**
	(14.07)	(10.90)	(16.16)	(21.22)	(2.48)
CEO salary	−0.01	−0.00	−0.01	−0.01	0.04***
	(−0.46)	(−0.08)	(−0.43)	(−1.36)	(5.23)
CEO ownership	−1.64	−0.86	−0.51	−0.92	−3.41***
	(−1.11)	(−0.56)	(−0.79)	(−1.25)	(−2.82)
CEO tenure	0.00	0.00	−0.00	−0.00	−0.00
	(0.9)	(0.52)	(−0.01)	(−0.01)	(−1.13)
CEO gender (c)	0.16	0.04	0.12*	0	0
	(1.24)	(0.27)	(1.89)		
CEO-chairman continuity	0.07	0.06	0.07***	0.07***	0.1***
	(1.63)	(1.30)	(2.71)	(3.42)	(7.51)
Board independence	0.09	−0.00	0.08	0.1	−0.57***
	(0.5)	(−0.02)	(0.76)	(1.06)	(−10.08)
Board female proportion	−0.42*	−0.45*	−0.13	−0.07	0.18**
	(−1.83)	(−1.64)	(−0.98)	(−0.79)	(2.23)
Board ownership	−0.71	−0.64	−0.97***	−1.16***	−4.03***
	(−1.56)	(−1.30)	(−3.1)	(−3.37)	(−16.32)
Firm size change	−0.00	−0.00	−0.002***	−0.00	−0.007***
	(−1.6)	(−1.26)	(−3.17)	(−1.02)	(−22.2)
Institutional ownership	−2.14*	−1.96	−1.97***	−2.23***	0.54
	(−1.78)	(−1.39)	(−2.78)	(−3.24)	(1.01)
Firm size	−0.00	−0.00	0.02	0.01	0.24***
	(−0.46)	(−0.21)	(1.28)	(1.32)	(5.91)
ROA	0.00	0.00	0.00	0.00	0.01***
	(0.58)	(0.44)	(0.59)	(0.11)	(17.04)
TMT's average social status		0.06* (1.95)	0.05*** (3.11)	0.03** (2.42)	0.08*** (2.79)
Observations	833	833	833	806	806
Wald-χ^2; Pseudo-R^2	214.57	262.85	15.93	19.96	1487.73

This variable is dropped from linear fixed-effect regression as it remains time-invariant in our sample within the window of our analysis; *z* statistics in parentheses.
$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

($b=-0.00$; insignificant). These combined results support Hypotheses 2 and 3. Indeed, these coefficients show that the social status of a firm's TMT increases the market value of its granted patents based on a subjective quality logic (H2). However, it does not affect the scientific value of the firm's granted patents based on an objective quality logic (H3).

4.1. Robustness checks

Several additional tests have been employed in order to assess the robustness of our main results. A key potential issue with our identification strategy could be endogeneity. In order to tackle this issue, we use three different approaches. First, to deal with potential reverse causality, that is, "aren't these the most innovative firms that hire the higher status TMT?" we use structural equation modeling introduced by Leszczensky and Wolbring (2019). This procedure involves the simultaneous estimation of two equations, where one of the equations is identical to our main model with logged numbers of patents as the dependent variable, and the other equation is the estimation of TMT social status using the same regressors in the main model plus the lag of the ultimate dependent variable in the main model. Before running structural equation modeling, we ran Durbin–Wu–Hausman and Granger causality tests. We implemented two Granger causality tests for panel data (Dumitrescu and Hurlin, 2012; Juodis

Table 5. Results from panel Poisson for predicting patent count within the extended dataset (2005–2014)

	(1)
Variables	Poisson
R&D spending	0.233***
	(18.50)
CEO salary	−0.0174
	(−0.996)
CEO ownership	−1.569
	(−1.447)
CEO tenure	0.00306
	(0.908)
CEO gender	0.00658
	(0.0692)
CEO-chairman continuity	0.0675*
	(1.938)
Board independence	0.0458
	(0.288)
Board female proportion	−0.449***
	(−2.775)
Board ownership	−1.760***
	(−3.846)
Firm size change	−0.000723
	(−0.771)
Institutional ownership	−2.580***
	(−2.697)
Firm size	−0.00651
	(−0.416)
ROA	0.000744
	(0.328)
TMT's average social status	0.0489**
	(2.308)
N	1,520
Wald-χ^2	373.15

z statistics in parentheses.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

et al., 2021) to support the decision of adopting an SEM to tackle reverse causality. We checked these tests on a balanced subset of the dataset, from 2005 to 2010, and both rejected the null hypothesis of no Granger causality (results are in Table 7). The results of structural equation modeling are presented in Table 8. Hypothesis 1 remains robust to structural equation modeling addressing reverse causality.

Second, we employ yet another method to deal with potential endogeneity caused by sample selection bias due to TMT social status and important variables such as firm size. Although we control for important determinants of firm patenting outcomes in line with prior research, there may still be concerns about the effect of such variables beyond the usual ways. For instance, it could be that "larger firms hire high-status TMT and obtain more patents through some hidden, bi-directional and complicated channels that resist removal by a simple panel regression (size effect)." In order to address this issue, we use the Heckman two-step selection model (Heckman, 1976), which has been widely used in prior research to deal with issues of the same nature (Velu and Jacob, 2016). The Heckman procedure, in our case, involves estimating dichotomized TMT social status[7] as a function of important and relevant controls in the main model predicting logged numbers of patents plus at least one variable that affects TMT social status but not firm patenting. This first stage allows us to obtain Lambda as a selection parameter. This selection parameter is then included in the second stage regression, which is identical to our main model predicting logged numbers of patents. We need to observe: (1) if the selection parameter is significant; and (2) if the estimations change. For the selection model, TMT social status is the dependent variable and all the controls in the main model predicting firm patenting (including firm size) – except for variables that are logically irrelevant, that is, R&D expenditure, CEO tenure, and institutional ownership – are included as regressors. Also, a variable related to TMT social status but not relevant to firm patenting is included in the selection model. We obtain this variable using the city in which a firm's headquarter was located and with the following logic: high-status TMTs are more likely to choose expensive cities. We identified 10 of the most expensive cities in the United States and a firm was assigned a variable called *Luxury*, which is a dummy taking 1, if the headquarter of the firm was located in one of these expensive cities and zero otherwise. This variable showed a significant correlation of 0.06 with TMT social status and a non-significant correlation of 0.01 with firm patenting. Year and industry dummies were also included in both stages. The results for the Heckman model are shown in Table 9. The selection parameter is insignificant, and Hypothesis 1 is still supported.

Third, we used propensity score matching to synthetically build a comparable control and treatment group with respect to variables included as a control in the main model predicting firm patenting. In order to do this, we first created a matching score based on the control variables of the main model, and then used the "psmatch2" procedure in Stata with a radius caliper of 0.2, to see whether the first hypothesis would still hold.[8] Table 10 shows that Hypothesis 1 is still robust.

The next set of robustness checks relates to our operationalization of key variables. First, although

Table 6. Results from seemingly unrelated regression predicting market and scientific value

	(1)	(2)	(3)	(4)
	Market value of patents	Market value of patents	Scientific value of patents	Scientific value of patents
R&D spending	0.06*** (15.07)	0.05*** (14.14)	0.007*** (9.62)	0.007*** (9.55)
CEO salary	0.01 (1.10)	0.01 (1.01)	−0.006** (−2.16)	−0.006** (−2.12)
CEO ownership	−0.95*** (−2.90)	−0.91*** (−2.78)	−0.22*** (−3.32)	−0.22*** (−3.36)
CEO tenure	0.005*** (3.93)	0.005*** (3.95)	0.001*** (5.68)	0.001*** (5.68)
CEO gender	−0.02 (−0.65)	−0.04 (−1.11)	0.005 (0.65)	0.007 (0.83)
CEO-chairman continuity	−0.02* (−0.65)	−0.02* (−1.70)	−0.00 (−0.26)	−0.00 (−0.24)
Board independence	0.03 (0.55)	0.01 (0.23)	0.01 (1.31)	0.01 (1.42)
Board female proportion	−0.05 (−0.74)	−0.05 (−0.76)	−0.02* (−1.78)	−0.02* (−1.77)
Board ownership	0.08 (0.94)	0.08 (0.95)	0.01 (0.72)	0.01 (0.72)
Firm size change	−0.001*** (−3.39)	−0.001*** (−3.31)	−0.00* (−1.74)	−0.00* (−1.78)
Institutional ownership	−0.76** (−2.29)	−0.75** (−2.28)	−0.02 (−0.41)	−0.02 (−0.42)
Firm size	−0.03*** (−5.52)	−0.03*** (−5.76)	−0.008*** (−6.99)	−0.008*** (−6.83)
ROA	0.005*** (6.48)	0.005*** (6.50)	−0.00* (−1.75)	−0.00* (−1.75)
TMT's average social status	–	0.01** (2.12)	–	−0.001 (−0.88)
N	833	833	833	833
R^2	32.12	32.97	18.01	18.35

z statistics in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

our measure of social status has been widely used and validated in prior research (as explained in the method section), we tried to construct an alternative measure of social status using the network size of TMT.[9] We ran our main regression with the network size of TMT replacing our main measure of TMT social status. Although the effect was far reduced, it was still significant and a positive predictor of patent count. Second, the measure we used in the main models was a composite measure. We therefore reran our main regression with each dimension of our composite measure of TMT social status. The results still show support for our hypotheses. Third, as our measure of social status was obtained as an average, it is also of interested to observe the individual TMT members' effect. We used the variance of TMT social status instead of our average measure in the main regression. The results remain robust. Table 11 shows the results of panel regressions with a logged count dependent variable and random effect for these different operationalizations of our measure of TMT social status.[10] Therefore, we can claim that our results are robust to alternative measures of social status. Similar robustness checks have been performed for Hypotheses 2 and 3 but for the sake of brevity have not been included. Results are available upon request.

Furthermore, we operationalized our dependent variable in different ways to check the robustness of our hypotheses. First, it could be argued that using only granted patents cannot adequately capture the nature of the innovativeness of the firm. We therefore retrieved patent applications for our window of analysis and replaced the granted patent count with the applied patent count (that are granted at a later date) within this window (2005–2010), in our analysis. Table 12

Table 7. Granger causality and Durbin–Wu–Hausman tests

Dumitrescu and Hurlin (2012) Granger non-causality test
H0: TMT status does not Granger-cause lnpat
H1: TMT status does Granger-cause lnpat for at least one panel (permno)
Optimal number of lags (AIC): 1 (lags tested: 1 to 1)
W-bar = 1.9190
Z-bar = 5.3979 (*p*-value = 0.0000)
H0: lnpat does not Granger-cause TMT status
H1: lnpat does Granger-cause TMT status for at least one panel (permno)
Optimal number of lags (AIC): 1 (lags tested: 1 to 1)
W-bar = 2.2134
Z-bar = 7.1273 (*p*-value = 0.0000)
Juodis et al. (2021) Granger non-causality test
H0: TMT status does not Granger-cause lnpat
H1: TMT status does Granger-cause lnpat for at least one panelvar
HPJ Wald test: 51.3765
p-value: 0.0000
H0: lnpat does not Granger-cause TMT status
H1: lnpat does Granger-cause TMT status for at least one panelvar
HPJ Wald test: 13.0529
p-value: 0.0015
Tests of endogeneity (Durbin–Wu–Hausman, 1954, 1973, and 1978)
H0: variables are exogenous
Durbin (score) $\chi^2(1) = 230.524$ ($p = 0.0000$)
Wu–Hausman $F(1, 830) = 317.582$ ($p = 0.0000$)

Table 7 displays the Granger causality and endogeneity tests to support the estimation of the SEM model. In all tests, we reject the null hypotheses of non-Granger causality and exogeneity.

Table 8. Structural modeling

	(1)	(2)
	TMT average status	Patent count
TMT's average social status		0.23** (2.4)
Patent count	−0.00 (−0.32)	
ROA	−0.00 (−0.25)	0.008 (0.99)
R&D spending	0.13*** (5.29)	0.51*** (7.54)
CEO salary	0.05 (0.92)	−0.22 (−1.36)
CEO ownership	−3.73*** (−2.98)	−1.55 (−0.45)
CEO tenure	0.00 (0.68)	−0.009 (−0.63)
CEO gender	0.89*** (5.27)	0.36 (0.76)
CEO-chairman continuity	0.09* (1.78)	0.22 (1.5)
Board independence	0.59*** (2.66)	−2.06*** (−3.33)
Board female proportion	0.05 (0.2)	−0.42 (−0.53)
Board ownership	−0.08 (−0.19)	−2.95** (−2.41)
Firm size change	−0.00 (−0.87)	−0.01*** (−5.49)
Institutional ownership	0.81 (0.62)	−3.05 (−0.84)
Firm size	0.06* (1.87)	0.01 (1.14)
Overall *N* (both models)	833	
Overall log-likelihood (both models)	5,256.56	

z statistics in parentheses.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

shows that Hypothesis 1 is still supported after this different operationalization. For Hypotheses 2 and 3, one may suspect that considering citations limited to the window of analysis may be insufficient. We, therefore, retrieved updated citation data up to 2020 for the patents within our window of analysis and used it in our main models instead of citation data up to 2010. Table 13 shows that Hypotheses 2 and 3 are robust to this different operationalization.

Finally, we address an issue regarding contextual effects. One may be interested in the effect of the financial crisis on our hypotheses. We did this by using a crisis dummy taking 1 if the observation year was after 2007 and zero otherwise. Table 14 (Poisson) shows that Hypothesis 1 is still robust and that the financial crisis does not affect our empirical analysis. Similar tests have been carried out for Hypotheses 2 and 3 but are not reported here for the sake of brevity.

5. Discussion

5.1. Theoretical implications

Considering the innovation of firms from a social perspective, the present paper fills the gap in an under-investigated research area that bridges two distinct (yet intertwined) streams of literature: innovation and TMT social status. In fact, we first unveil that the social status of TMT is positively associated with innovation (operationalized by the number of patents granted) for focal firms, because high-status TMTs are likely to detain a superior ability to convey resources for R&D, which, in turn, are fueling innovation. In particular, this phenomenon unfolds because the high-status wield a multi-faceted influence on a firm's innovation trajectory, including status-related

Table 9. Heckman selection

	(1)	(2)
	Dichotomized TMT status	Patent count
R&D spending		0.64*** (14.84)
CEO salary	0.18 (1.45)	−0.01 (−0.07)
CEO ownership	−12.06*** (−2.66)	−21.94 (−1.37)
CEO tenure		0.02 (1.52)
CEO gender	0.00 (0.03)	0.41 (0.98)
CEO-chairman continuity	0.19* (1.75)	0.10 (0.42)
Board independence	0.77 (1.64)	0.68 (0.71)
Board female proportion	0.68 (1.25)	0.25 (0.26)
Board ownership	−1.12* (−1.71)	−2.56 (−1.37)
Firm size change		−0.008** (−2.36)
Institutional ownership		−7.60* (−1.95)
Firm size	0.22*** (5.19)	0.17 (0.86)
ROA	−0.00 (−1.13)	0.008 (0.70)
TMT's average social status		0.23** (2.17)
Lambda (selection parameter)		1.15 (0.79)
Luxury	0.12* (0.91)	
Overall *N* (both models)		833 (427 censored)
Overall Wald-χ^2 (both models)		308.52

z statistics in parentheses.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

strategic leadership capabilities (O'Reilly et al., 2014) that foster an environment conducive to innovative endeavors, robust support structures that optimize resource allocation and utilization for innovative initiatives (Nadkarni and Chen, 2014), and a superior ability to attract and integrate top-tier talent, which enhances the firm's innovative capacity (Elenkov and Manev, 2005). In addition, the same high-status TMTs tend to be more risk-prone: R&D activities, by definition, involve some degree of risk, so it is also a fundamental attitude to promote R&D investments. This complements the literature that links tangible and intangible resources with innovation outcomes (e.g., Sievinen et al., 2020). Similarly, we add empirical validation to the literature that assesses TMT status in terms of realization of innovation opportunities (e.g., Ling et al., 2008; Rovelli et al., 2020), confirming that on average a higher-risk propensity is expected to increase innovation outcome.

While the aforementioned result also reinforces the well-known idea that additional R&D resources (deployed by high-status TMT) on average increase innovation (e.g., Song et al., 2006; Grigoriou and Rothaermel, 2017), we claim that our key contribution relates mostly to understanding what type of innovation is expected to be fueled depending on TMT status.

Thus, our core theoretical contribution consists in assessing how TMT status can impact the quality of the same innovation, and not only its amount. In this context, we find that TMT social status increases the market value of granted patents (H2) but has no or negligible impact on the scientific value of these patents (H3). These findings fill the existing gap in the role of social-related characteristics (status, in our case) played in firms' innovation. In fact, previous innovation literature almost exclusively focuses on the characteristics of inventors rather than top executives (Schumpeter and Nichol, 1934; Nelson and Winter, 1982; Uzzi, 1996; Guan and Liu, 2016).

We acknowledge that prior research has evidenced the importance of inter- and

Table 10. Propensity score matching for the effect of TMT's status on patent count

Variable	Sample	Treated	Controls	Difference	S.E.	*T*-stat
Logged number of patents	Unmatched	3.80	2.66	1.14	0.11	10.27
	ATT	3.80	3.48	0.31	0.12	2.48

psmatch2: Treatment assignment	psmatch2: Common support on support	Total
Untreated	427	427
Treated	406	406
Total	833	833

S.E. does not take into account that the propensity score is estimated.

Table 11. Panel regression count variable with random effects (status operationalizations)

	(1)	(2)	(3)	(4)
	Patent count	Patent count	Patent count	Patent count
R&D spending	0.36*** (7.88)	0.37*** (8.22)	0.37*** (8.06)	0.20*** (3.33)
CEO salary	0.03 (0.70)	0.04 (0.73)	0.04 (0.77)	0.05 (1.01)
CEO ownership	0.23 (0.09)	−0.46 (−0.22)	−0.63 (−0.30)	−1.47 (−0.73)
CEO tenure	0.003 (0.51)	0.005 (0.88)	0.006 (0.99)	0.008 (1.26)
CEO gender	0.15 (0.26)	−0.26 (−0.42)	0.02 (0.05)	0.19 (0.31)
CEO-chairman continuity	0.14*** (2.68)	0.14*** (2.66)	0.14*** (2.67)	0.09* (1.73)
Board independence	−0.85*** (−3.77)	−0.87*** (−3.92)	−0.89*** (−3.99)	−0.30 (−1.28)
Board female proportion	−0.70* (−1.81)	−0.67* (−1.79)	−0.67* (−1.78)	−0.44 (−1.18)
Board ownership	−0.62 (−1.42)	−0.56 (−1.31)	−0.60 (−1.40)	−0.36 (−0.85)
Firm size change	−0.003*** (−3.64)	−0.003*** (−3.85)	−0.003*** (−3.78)	−0.005*** (−4.91)
Institutional ownership	0.38 (0.22)	0.32 (0.19)	0.44 (0.25)	−0.66 (−0.37)
Firm size	0.18*** (2.99)	0.18*** (2.99)	0.18*** (3.00)	0.47*** (5.63)
ROA	0.002 (0.72)	0.002 (0.87)	0.002 (0.81)	0.001 (0.39)
TMT's average network size	0.0001** (2.13)	–	–	–
Variance of TMT social status	–	0.13** (2.42)	–	–
Outside directorship	–	–	0.10* (1.76)	–
Educational credentials	–	–		0.23** (2.24)
N	833	833	833	833
R^2	52.20	–	–	–
Wald-χ^2	–	191.83	187.61	231.75

z statistics in parentheses.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

intra-organizational connections among inner actors for firm innovation, for example, claiming that inventors who are supposedly the primary players in generating patents are deeply influenced by the social context within which they operate (Gulati, 1998; Welsh et al., 2008; Schweisfurth and Herstatt, 2016; Tomlinson and Fai, 2016). However, this literature largely neglects how TMT social attributes can determine the nature of the innovation of focal firms (Talke et al., 2010).

Our findings show that ignoring how TMT social attributes (such as TMT status) affect innovation may prevent the acquisition of a more comprehensive view of how status impacts organizational dimensions, which is an important goal for TMT scholars (e.g., Hambrick and Mason, 1984; Ahuja and Morris Lampert, 2001; Hambrick, 2007). Our research thus shows the effects of one important attribute of TMT social dimension, that is, TMT social status, on firm patenting, as a proxy for innovation. Therefore, we build on the TMT social status literature (e.g., Rovelli et al., 2020; Sievinen et al., 2020) by theorizing and finding that TMT social status impacts the quality of innovation generated by the same firm.

Table 12. Negative binomial for applied patents

	(1)
	Patent count
R&D spending	0.210259*** (4.28)
CEO salary	0.027194 (1.38)
CEO ownership	0.52286 (0.30)
CEO tenure	0.003604 (0.74)
CEO gender	0.595947 (1.14)
CEO-chairman continuity	−0.00985 (−0.27)
Board independence	−0.0727 (−0.45)
Board female proportion	−0.14669 (−0.52)
Board ownership	0.280877 (0.58)
Firm size change	0.00 (0.06)
Institutional ownership	−1.4986 (−1.11)
Firm size	0.119403** (2.00)
ROA	0.007708*** (2.99)
TMT's average social status	0.065187* (1.65)
N	780
Wald-χ^2	208.9

z statistics in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 13. Surge with patent citations tracked to 2020

	(1)	(2)
	Market value of patents	Scientific value of patents
R&D spending	0.08*** (14.71)	0.22*** (7.99)
CEO salary	0.01 (1.07)	0.05 (0.81)
CEO ownership	−0.37 (−1.25)	0.69 (0.48)
CEO tenure	0.002** (2.09)	−0.002 (−0.45)
CEO gender	0.01 (0.29)	0.21 (1.07)
CEO-chairman continuity	−0.01 (−1.15)	0.21*** (3.34)
Board independence	−0.05 (−0.94)	−0.64** (−2.43)
Board female proportion	0.09 (1.35)	−0.14 (−0.44)
Board ownership	−0.09 (−0.93)	−0.16 (−0.34)
Firm size change	−0.001*** (−3.64)	0.001 (0.86)
Institutional ownership	−0.85*** (−2.75)	−0.18 (−0.13)
Firm size	−0.07*** (−9.54)	−0.20*** (−5.19)
ROA	0.004*** (6.07)	−0.009** (2.54)
TMT's average social status	0.02*** (2.78)	−0.05 (−1.47)
N	833	833
R^2	50.0	31.47

z statistics in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

More specifically, prior research shows that TMT dispositional attributes affect firms' innovation outcomes (Nadkarni and Chen, 2014; Cummings and Knott, 2018). Yet, almost absent in this line of research is the role of the situational attributes of TMT, such as their social attributes on innovation (Daellenbach et al., 1999; Liu et al., 2012; Ahn et al., 2017; Chung et al., 2018; Boone et al., 2019; Belderbos et al., 2020). We complement this research stream by integrating both dispositional and situational attributes; in this way, we explain the nature of firms' innovation considering both sides, providing a more comprehensive picture of the phenomenon (Van de Wal et al., 2020), responding to a call to fill this research gap (e.g., Lovelace et al., 2018).

Finally, our paper sheds additional light on the role played by social status within organizations. There is a nearly ubiquitous consensus that social status increases audiences' perception of an agent's quality (subjective quality), but the latter is distinct from objective quality (Piazza and Castellucci, 2014; Anderson et al., 2015; Mahadevan et al., 2019). However, this is a complex and controversial issue that may have a heterogeneous impact in differing contexts (Merton, 1972; Benjamin and Podolny, 1999; Wang et al., 2014; Pollock et al., 2015; Cao and Smith, 2021). We extend prior research by showing that within the innovation context, TMT social status is linked to subjective quality of innovation, but the same does not impact the objective quality of innovation.

5.2. *Managerial implications*

Our paper also has practical implications. In particular, shareholders can benefit from our findings when designing TMT composition. In fact, while the status

Table 14. Poisson financial crisis effects on granted patents' count

	(1)
	Patent count
R&D spending	0.21*** (3.35)
CEO salary	0.04 (0.75)
CEO ownership	−1.66 (−0.82)
CEO tenure	0.006 (1.05)
CEO gender	0.18 (0.29)
CEO-chairman continuity	0.16*** (3.07)
Board independence	−0.52** (−2.28)
Board female proportion	−0.50 (−1.35)
Board ownership	−0.29 (−0.68)
Firm size change	−0.005*** (−5.48)
Institutional ownership	0.03 (0.02)
Firm size	0.44*** (5.39)
ROA	0.001 (0.44)
Financial crisis	−0.23 (−1.17)
TMT's average social status	0.21** (1.96)
Financial crisis × TMT's average social status	0.003 (0.04)
N	833
Wald-χ^2	316.43

z statistics in parentheses.
*$p<0.1$; **$p<0.05$; ***$p<0.01$.

of TMT members itself cannot be easily manipulated in the short term, the composition of a TMT can be adjusted relatively quickly and eventually reformulated. Accordingly, our findings show that adding high-status managers to TMT increases innovation output and – what is expected to be even more important for for-profit firms – its market value. However, especially for non-profit organizations or social enterprises, where the scientific value of innovation may be more important than its market value, our findings suggest that investing in high-status TMT members may not be very effective (except for the absolute value of innovation). This presents an intriguing trade-off: when the goal is focused on increasing market value, selecting a high-status board member or CEO is desired, but when the goal is to increase scientific depth, this may not be the most effective strategic decision.

Our paper also has implications for status-aspiring behavior by TMT members. Clearly, social status is a desired attribute for managers, and therefore, our results simply enhance the value of this attribute, evidencing the positive relationships with additional innovation and its related market value. However, the fact that TMT status is not a predictor of the scientific value of innovation offers intriguing reasoning opportunities. In particular, managers should try to compensate for the lack of correlation of objective quality to social status by improving their own objective and "skills-based" competence, when particularly required, such as in the case of social enterprises or research institutions. In other words, the task facing a manager who wants to perform well in innovation (according to both the scientific and market dimensions) is to fight ego power and deception caused by social respect: a manager should not assume that social respect means that he/she is objectively very competent. However, as mentioned in the theory and hypotheses chapter, overperforming in terms of scientific value may legitimately not be a priority for most TMTs who manage traditional for-profit firms.

5.3. Limitations and further avenues for future research

Our study has its own limitations that nevertheless offer directions for future research. First, our empirical analyses rely on manufacturing firms among the S&P 1500 constituents. Future research should also investigate the generalizability of our theory and findings in other industries. In addition, by conducting sample splits by industries, we find that some industries show a stronger relationship between TMT social status and patent count (Hypothesis 1). However, we decided not to include this result as the subsamples falling in some industries were too small. Theoretically speaking, we suspect that for industries where hard-core science is needed for innovation, the effect of status is stronger because resource and opportunity channels (which are core elements for our theoretical speculation) can act as key assets when complexity and difficulty levels segregate firms. Still, this may be debatable and we encourage additional empirical studies in this regard. However, we claim that our study has some external validity as we do not deeply focus on industry-specific characteristics and peculiarities.

Second, while our study is among the first to link a social attribute (status) of TMT to innovation outcome, it does not distinguish CEOs from other TMT members. Future studies can disentangle the innovation effects of high-status CEOs from other TMT members, perhaps incorporating agent-principal issues in this relationship. In fact, it is rational to assume that CEOs may have a different weight with respect to other TMT members.

Third, while we used rigorous methods for endogeneity control, and various model specifications following prior relevant research (Daellenbach et al., 1999; Liu et al., 2012; Ahn et al., 2017; Chang et al., 2019; Van de Wal et al., 2020), at the same time giving a boost to our construct validity as compared to prior research (Westphal and Shani, 2016), by using two measures of social status we did not incorporate network-level data with high levels of detail. For instance, it would be interesting to see how networks of TMT and inventors co-evolve.

In addition, based on our findings, we see an exciting opportunity to generate insights into the socio-cognitive framework within which TMTs affect firm innovation outcomes and to add explanatory power to upper-echelons theory. For instance, we suspect that TMT social status could have unique and complex impacts on firm innovation outcomes when considered jointly with TMT dispositional risk-taking determinants, such as tenure. Tenure is generally found to reduce risk-taking due to horizon problems associated with it (Matta and Beamish, 2008), but social status may eventually compensate for these horizon-related issues by improving resources and opportunities at the disposal of TMTs. Therefore, we encourage further research endeavors aimed at unveiling how the joint effect of TMT social status and tenure affects innovation.

Finally, since higher-status TMTs are more likely to invest in risky activities, such as R&D, it may be reasonable to expect TMT status to also affect other patents' characteristics, such as whether they tend to all belong to similar technological classes or not. This could be assessed by considering the different technological classes of patents issued (e.g., Yan and Luo, 2017). We encourage future research endeavors aimed at clarifying how TMT status impacts that and other patents' dimensions.[11]

To conclude, our study sheds some light on how TMT status affects the innovation process in focal firms led by that TMT. We show that high-status TMTs tend to generate more and better innovation in terms of its market value, but this positive link vanishes if the scientific value of innovation is considered. With our findings, we hope to stimulate and enrich the scholarly conversation on how TMT status impacts different organizational dimensions, including innovation.

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Data availability statement

The data that support the findings of this study are available on request from the authors. The data are not publicly available due to privacy or ethical restrictions.

References

Ahn, J.M., Minshall, T., and Mortara, L. (2017) Understanding the human side of openness: the fit between open innovation modes and CEO characteristics. *R&D Management*, **47**, 5, 727–740.

Ahuja, G. and Katila, R. (2001) Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. *Strategic Management Journal*, **22**, 3, 197–220.

Ahuja, G. and Morris Lampert, C. (2001) Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, **22**, 6–7, 521–543.

Alexiev, A.S., Jansen, J.J., Van den Bosch, F.A., and Volberda, H.W. (2010) Top management team advice seeking and exploratory innovation: the moderating role of TMT heterogeneity. *Journal of Management Studies*, **47**, 7, 1343–1364.

Allen, T.J. and Katz, R. (1992) Age, education and the technical ladder. *IEEE Transactions on Engineering Management*, **39**, 3, 237–245.

Anderson, C., Hildreth, J.A.D., and Howland, L. (2015) Is the desire for status a fundamental human motive? A review of the empirical literature. *Psychological Bulletin*, **141**, 3, 574–601.

Arora, A., Belenzon, S., and Patacconi, A. (2018) The decline of science in corporate R&D. *Strategic Management Journal*, **39**, 1, 3–32.

Arora, A., Belenzon, S., and Suh, J. (2022) Science and the market for technology. *Management Science*, Forthcoming.

Arroyabe, M.F., Hussinger, K., and Hagedoorn, J. (2020) Hiring new key inventors to improve firms' post-M&A inventive output. *R&D Management*, **50**, 4, 494–509.

Astley, W.G. (1985) The two ecologies: population and community perspectives on organizational evolution. *Administrative Science Quarterly*, **30**, 224–241.

Audretsch, D.B. and Feldman, M.P. (1996) R&D spillovers and the geography of innovation and production. *The American Economic Review*, **86**, 3, 630–640.

Autio, E., Sapienza, H.J., and Almeida, J.G. (2000) Effects of age at entry, knowledge intensity, and imitability on international growth. *Academy of Management Journal*, **43**, 5, 909–924.

Belderbos, R., Du, H.S., and Slangen, A. (2020) When do firms choose global cities as foreign investment locations within countries? The roles of contextual distance, knowledge intensity, and target-country experience. *Journal of World Business*, **55**, 1, 101022.

Benartzi, S. and Thaler, R.H. (1999) Risk aversion or myopia? Choices in repeated gambles and retirement investments. *Management Science*, **45**, 3, 364–381.

Benjamin, B.A. and Podolny, J.M. (1999) Status, quality, and social order in the California wine industry. *Administrative Science Quarterly*, **44**, 3, 563–589.

Berry, H. (2014) Global integration and innovation: multicountry knowledge generation within MNCs. *Strategic Management Journal*, **35**, 6, 869–890.

Bettis, R., Gambardella, A., Helfat, C., and Mitchell, W. (2014) Quantitative empirical analysis in strategic management. *Strategic Management Journal*, **35**, 7, 949–953.

Bidwell, M., Won, S., Barbulescu, R., and Mollick, E. (2015) I used to work at Goldman Sachs! How firms benefit from organizational status in the market for human capital. *Strategic Management Journal*, **36**, 8, 1164–1173.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013) Identifying technology spillovers and product market rivalry. *Econometrica*, **81**, 4, 1347–1393.

Blundell, R., Griffith, R., and Reenen, J.V. (1995) Dynamic count data models of technological innovation. *The Economic Journal*, **105**, 429, 333–344.

Blundell, R., Griffith, R., and Reenen, J.V. (2002) Individual effects and dynamics in count data models. *Journal of Econometrics*, **108**, 113–131.

Boone, C., Lokshin, B., Guenter, H., and Belderbos, R. (2019) Top management team nationality diversity, corporate entrepreneurship, and innovation in multinational firms. *Strategic Management Journal*, **40**, 2, 277–302.

Bozeman, B. and Rogers, J.D. (2002) A churn model of scientific knowledge value: Internet researchers as a knowledge value collective. *Research Policy*, **31**, 5, 769–794.

Bromiley, P. and Rau, D. (2016) Social, behavioral, and cognitive influences on upper echelons during strategy process: a literature review. *Journal of Management*, **42**, 1, 174–202.

Bromiley, P., Rau, D., and Zhang, Y. (2017) Is R & D risky? *Strategic Management Journal*, **38**, 4, 876–891.

Bunderson, J.S. and Reagans, R.E. (2011) Power, status, and learning in organizations. *Organization Science*, **22**, 5, 1182–1194.

Cao, J. and Smith, E.B. (2021) Why do high-status people have larger social networks? Belief in status-quality coupling as a driver of network-broadening behavior and social network size. *Organization Science*, **32**, 1, 111–132.

Cao, Q., Simsek, Z., and Jansen, J.J. (2015) CEO social capital and entrepreneurial orientation of the firm: bonding and bridging effects. *Journal of Management*, **41**, 7, 1957–1981.

Capaldo, A., Lavie, D., and Messeni Petruzzelli, A. (2017) Knowledge maturity and the scientific value of innovations: the roles of knowledge distance and adoption. *Journal of Management*, **43**, 2, 503–533.

Chang, H.Y., Lee, C.Y., and Wong, Y.J. (2019) The impact of earnings pressure on exploratory innovation. *R&D Management*, **49**, 4, 470–483.

Chappin, M., Faber, J., and Meeus, M. (2019) Learning patterns in early stage R&D projects: empirical evidence from the fibre raw material technology project in The Netherlands. *R&D Management*, **49**, 4, 684–695.

Chung, D., Cho, T.S., and Kang, J. (2018) The linkage between TMT knowledge diversity and firm-level innovation: the role of organisational search scope and managerial discretion. *International Journal of Technology Management*, **78**, 3, 208–233.

Clark, K.D. and Maggitti, P.G. (2012) TMT potency and strategic decision-making in high technology firms. *Journal of Management Studies*, **49**, 7, 1168–1193.

Cohen, W.M. and Levin, R.C. (1989) Empirical studies of innovation and market structure. *Handbook of Industrial Organization*, **2**, 1059–1107.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, **35**, 128–152.

Cohn, J.B., Liu, Z., and Wardlaw, M.I. (2022) Count (and count-like) data in finance. *Journal of Financial Economics*, **146**, 2, 529–551.

Conti, R. (2014) Do non-competition agreements lead firms to pursue risky R&D projects? *Strategic Management Journal*, **35**, 8, 1230–1248.

Conti, R., Gambardella, A., and Mariani, M. (2014) Learning to be Edison: inventors, organizations, and breakthrough inventions. *Organization Science*, **25**, 3, 833–849.

Cummings, T. and Knott, A.M. (2018) Outside CEOs and innovation. *Strategic Management Journal*, **39**, 8, 2095–2119.

Daellenbach, U.S., McCarthy, A.M., and Schoenecker, T.S. (1999) Commitment to innovation: the impact of top management team characteristics. *R&D Management*, **29**, 3, 199–208.

De Mattos, C., Burgess, T.F., and Shaw, N.E. (2013) The impact of R&D-specific factors on the attractiveness of small-and medium-sized enterprises as partners vis-à-vis alliance formation in large emerging economies. *R&D Management*, **43**, 1, 1–20.

Dechow, P.M. and Sloan, R.G. (1991) Executive incentives and the horizon problem: an empirical investigation. *Journal of Accounting and Economics*, **14**, 1, 51–89.

Demirkan, I. and Demirkan, S. (2012) Network characteristics and patenting in biotechnology, 1990–2006. *Journal of Management*, **38**, 6, 1892–1927.

Denicolai, S., Ramirez, M., and Tidd, J. (2014) Creating and capturing value from external knowledge:

the moderating role of knowledge intensity. *R&D Management*, **44**, 3, 248–264.

Dimov, D., Shepherd, D.A., and Sutcliffe, K.M. (2007) Requisite expertise, firm reputation, and status in venture capital investment allocation decisions. *Journal of Business Venturing*, **22**, 4, 481–502.

Dumitrescu, E.I. and Hurlin, C. (2012) Testing for granger non-causality in heterogeneous panels. *Economic Modelling*, **29**, 4, 1450–1460.

Elenkov, D.S. and Manev, I.M. (2005) Top management leadership and influence on innovation: the role of sociocultural context. *Journal of Management*, **31**, 3, 381–402.

Felin, T. and Hesterly, W.S. (2007) The knowledge-based view, nested heterogeneity, and new value creation: philosophical considerations on the locus of knowledge. *Academy of Management Review*, **32**, 1, 195–218.

Fich, E.M., Nguyen, T., and Petmezas, D. (2023) The effects of terrorist attacks on inventor productivity and mobility. *Research Policy*, **52**, 1, 104655.

Fiebig, D.G. (2001) Seemingly unrelated regression. In: Editor, Baltagi, B.H., *A Companion to Theoretical Econometrics*. Malden: Blackwell, pp. 101–121.

Flickinger, M., Wrage, M., Tuschke, A., and Bresser, R. (2016) How CEOs protect themselves against dismissal: a social status perspective. *Strategic Management Journal*, **37**, 6, 1107–1117.

Geuna, A. and Nesta, L.J. (2006) University patenting and its effects on academic research: the emerging European evidence. *Research Policy*, **35**, 6, 790–807.

Granovetter, M. (1985) Economic action and social structure: the problem of embeddedness. *American Journal of Sociology*, **91**, 3, 481–510.

Greene, W.H. (2003) *Econometric Analysis*. Pearson Education India, Delhi

Grigoriou, K. and Rothaermel, F.T. (2017) Organizing for knowledge generation: internal knowledge networks and the contingent effect of external knowledge sourcing. *Strategic Management Journal*, **38**, 2, 395–414.

Guan, J. and Liu, N. (2016) Exploitative and exploratory innovations in knowledge network and collaboration network: a patent analysis in the technological field of nano-energy. *Research Policy*, **45**, 1, 97–112.

Gulati, R. (1998) Alliances and networks. *Strategic Management Journal*, **19**, 4, 293–317.

Haas, M.R. and Hansen, M.T. (2007) Different knowledge, different benefits: toward a productivity perspective on knowledge sharing in organizations. *Strategic Management Journal*, **28**, 11, 1133–1153.

Hambrick, D.C. (2007) The field of management's devotion to theory: too much of a good thing? *Academy of Management Journal*, **50**, 6, 1346–1352.

Hambrick, D.C. and Mason, P.A. (1984) Upper echelons: the organization as a reflection of its top managers. *Academy of Management Review*, **9**, 2, 193–206.

Heckman, J.J. (1976) A life-cycle model of earnings, learning, and consumption. *Journal of Political Economy*, **84**, 4, Part 2, S9–S44.

Hilbe, J.M. (2011) *Negative Binomial Regression*. New York: Cambridge University Press.

Howells, J., James, A., and Malik, K. (2003) The sourcing of technological knowledge: distributed innovation processes and dynamic change. *R&D Management*, **33**, 4, 395–409.

Hudon, M., Labie, M., and Reichert, P. (2020) What is a fair level of profit for social enterprise? Insights from microfinance. *Journal of Business Ethics*, **162**, 3, 627–644.

Hussinger, K. and Pacher, S. (2019) Information ambiguity, patents and the market value of innovative assets. *Research Policy*, **48**, 3, 665–675.

Juodis, A., Karavias, Y., and Sarafidis, V. (2021) A homogeneous approach to testing for granger non-causality in heterogeneous panels. *Empirical Economics*, **60**, 1, 93–112.

Kalnins, A. (2018) Multicollinearity: how common factors cause type 1 errors in multivariate regression. *Strategic Management Journal*, **39**, 8, 2362–2385.

Kane, A.A., Argote, L., and Levine, J.M. (2005) Knowledge transfer between groups via personnel rotation: effects of social identity and knowledge quality. *Organizational Behavior and Human Decision Processes*, **96**, 1, 56–71.

Katila, R. and Chen, E.L. (2008) Effects of search timing on innovation: the value of not being in sync with rivals. *Administrative Science Quarterly*, **53**, 4, 593–625.

Kehoe, R.R. and Tzabbar, D. (2015) Lighting the way or stealing the shine? An examination of the duality in star scientists' effects on firm innovative performance. *Strategic Management Journal*, **36**, 5, 709–727.

Keum, D.D. (2021) Innovation, short-termism, and the cost of strong corporate governance. *Strategic Management Journal*, **42**, 1, 3–29.

Kim, B. and Oh, H. (2002) Economic compensation compositions preferred by R&D personnel of different R&D types and intrinsic values. *R&D Management*, **32**, 1, 47–59.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017) Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, **132**, 2, 665–712.

Kogut, B. and Zander, U. (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, **3**, 3, 383–397.

Lahiri, N. (2010) Geographic distribution of R&D activity: how does it affect innovation quality? *Academy of Management Journal*, **53**, 5, 1194–1209.

Lenski, G.E. (1954) Status crystallization: a non-vertical dimension of social status. *American Sociological Review*, **19**, 4, 405–413.

Leszczensky, L. and Wolbring, T. (2019) How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study. *Sociological Methods & Research*, **51**, 2, 837–865.

Li, K., Qiu, J., and Wang, J. (2019) Technology conglomeration, strategic alliances, and corporate innovation. *Management Science*, **65**, 11, 5065–5090.

Libaers, D. (2017) Time allocations across collaborations of academic scientists and their impact on efforts to commercialize novel technologies: is more always better? *R&D Management*, **47**, 2, 180–197.

Lin, B.W. and Chen, J.S. (2005) Corporate technology portfolios and R&D performance measures: a study of technology intensive firms. *R&D Management*, **35**, 2, 157–170.

Ling, Y.A.N., Simsek, Z., Lubatkin, M.H., and Veiga, J.F. (2008) Transformational leadership's role in promoting corporate entrepreneurship: examining the CEO-TMT interface. *Academy of Management Journal*, **51**, 3, 557–576.

Liu, K., Li, J., Hesterly, W., and Cannella, A., Jr. (2012) Top management team tenure and technological inventions at post-IPO biotechnology firms. *Journal of Business Research*, **65**, 9, 1349–1356.

Liu, Z., Huang, Y., Huang, Y., Song, Y.A., and Kumar, A. (2022) How does one-sided versus two-sided customer orientation affect B2B platform's innovation: differential effects with top management team status. *Journal of Business Research*, **141**, 619–632.

Lovelace, J.B., Bundy, J., Hambrick, D.C., and Pollock, T.G. (2018) The shackles of CEO celebrity: sociocognitive and behavioral role constraints on "star" leaders. *Academy of Management Review*, **43**, 3, 419–444.

Lüthje, C. and Franke, N. (2003) The 'making' of an entrepreneur: testing a model of entrepreneurial intent among engineering students at MIT. *R&D Management*, **33**, 2, 135–147.

MacCrimmon, K.R. and Wehrung, D.A. (1990) Characteristics of risk taking executives. *Management Science*, **36**, 4, 422–435.

Magee, J.C. and Galinsky, A.D. (2008) 8 social hierarchy: the self-reinforcing nature of power and status. *Academy of Management Annals*, **2**, 1, 351–398.

Mahadevan, N., Gregg, A.P., and Sedikides, C. (2019) Is self-regard a sociometer or a hierometer? Self-esteem tracks status and inclusion, narcissism tracks status. *Journal of Personality and Social Psychology*, **116**, 3, 444–466.

Matta, E. and Beamish, P.W. (2008) The accentuated CEO career horizon problem: evidence from international acquisitions. *Strategic Management Journal*, **29**, 7, 683–700.

McCarthy, I.P. and Gordon, B.R. (2011) Achieving contextual ambidexterity in R&D organizations: a management control system approach. *R&D Management*, **41**, 3, 240–258.

Medcof, J.W. (2008) The organizational influence of the chief technology officer. *R&D Management*, **38**, 4, 406–420.

Merton, R.K. (1972) Insiders and outsiders: a chapter in the sociology of knowledge. *American Journal of Sociology*, **78**, 1, 9–47.

Minichilli, A., Corbetta, G., and MacMillan, I.C. (2010) Top management teams in family-controlled companies: 'familiness', 'faultlines', and their impact on financial performance. *Journal of Management Studies*, **47**, 2, 205–222.

Moehrle, M.G., Walter, L., Geritz, A., and Müller, S. (2005) Patent-based inventor profiles as a basis for human resource decisions in research and development. *R&D Management*, **35**, 5, 513–524.

Mueller, V., Rosenbusch, N., and Bausch, A. (2013) Success patterns of exploratory and exploitative innovation: a meta-analysis of the influence of institutional factors. *Journal of Management*, **39**, 6, 1606–1636.

Nadkarni, S. and Chen, J. (2014) Bridging yesterday, today, and tomorrow: CEO temporal focus, environmental dynamism, and rate of new product introduction. *Academy of Management Journal*, **57**, 6, 1810–1833.

Nelson, R.R. and Winter, S.G. (1982) The Schumpeterian tradeoff revisited. *The American Economic Review*, **72**, 1, 114–132.

Nesta, L. and Saviotti, P.P. (2006) Firm knowledge and market value in biotechnology. *Industrial and Corporate Change*, **15**, 4, 625–652.

O'Reilly, C.A., III, Caldwell, D.F., Chatman, J.A., and Doerr, B. (2014) The promise and problems of organizational culture: CEO personality, culture, and firm performance. *Group & Organization Management*, **39**, 6, 595–625.

Palomeras, N. and Melero, E. (2010) Markets for inventors: learning-by-hiring as a driver of mobility. *Management Science*, **56**, 5, 881–895.

Perretti, F. and Negro, G. (2006) Filling empty seats: how status and organizational hierarchies affect exploration versus exploitation in team design. *Academy of Management Journal*, **49**, 4, 759–777.

Phene, A., Fladmoe-Lindquist, K., and Marsh, L. (2006) Breakthrough innovations in the US biotechnology industry: the effects of technological space and geographic origin. *Strategic Management Journal*, **27**, 4, 369–388.

Piazza, A. and Castellucci, F. (2014) Status in organization and management theory. *Journal of Management*, **40**, 1, 287–315.

Polanyi, K. and MacIver, R.M. (1944) *The great transformation*, Vol. **2**. Boston: Beacon Press, p. 145.

Pollock, T.G., Chen, G., Jackson, E.M., and Hambrick, D.C. (2010) How much prestige is enough? Assessing the value of multiple types of high-status affiliates for young firms. *Journal of Business Venturing*, **25**, 1, 6–23.

Pollock, T.G., Lee, P.M., Jin, K., and Lashley, K. (2015) (Un) tangled: exploring the asymmetric coevolution of new venture capital firms' reputation and status. *Administrative Science Quarterly*, **60**, 3, 482–517.

Priem, R.L. (1990) Top management team group factors, consensus, and firm performance. *Strategic Management Journal*, **11**, 6, 469–478.

Richard, O.C., Wu, J., Markoczy, L.A., and Chung, Y. (2019) Top management team demographic-faultline strength and strategic change: what role does environmental dynamism play? *Strategic Management Journal*, **40**, 6, 987–1009.

Rong, Z., Wu, X., and Boeing, P. (2017) The effect of institutional ownership on firm innovation: evidence from Chinese listed firms. *Research Policy*, **46**, 9, 1533–1551.

Rosenberg, L.J. and Czepiel, J.A. (1984) A marketing approach for customer retention. *Journal of Consumer Marketing*, **1**, 2, 45–51.

Rothaermel, F.T. and Boeker, W. (2008) Old technology meets new technology: complementarities, similarities, and alliance formation. *Strategic Management Journal*, **29**, 1, 47–77.

Rovelli, P., Rossi-Lamastra, C., Longoni, A., and Cagliano, R. (2020) TMT organizational configurations and opportunity realization in established firms: an exploratory analysis. *Long Range Planning*, **53**, 3, 101972.

Runge, S., Schwens, C., and Schulz, M. (2022) The invention performance implications of coopetition: how technological, geographical, and product market overlaps shape learning and competitive tension in R&D alliances. *Strategic Management Journal*, **43**, 2, 266–294.

Rynes, S.L., Bartunek, J.M., and Daft, R.L. (2001) Across the great divide: knowledge creation and transfer between practitioners and academics. *Academy of Management Journal*, **44**, 2, 340–355.

Schulze, A., Paul MacDuffie, J., and Täube, F.A. (2015) Introduction: knowledge generation and innovation diffusion in the global automotive industry—change and stability during turbulent times. *Industrial and Corporate Change*, **24**, 3, 603–611.

Schumpeter, J.A. and Nichol, A.J. (1934) Robinson's economics of imperfect competition. *Journal of Political Economy*, **42**, 2, 249–259.

Schweisfurth, T.G. and Herstatt, C. (2016) How internal users contribute to corporate product innovation: the case of embedded users. *R&D Management*, **46**, S1, 107–126.

Shang, S.S., Yao, C.Y., and Liou, D.M. (2017) The effects of knowledge interaction for business innovation. *R&D Management*, **47**, 3, 337–351.

Sievinen, H.M., Ikäheimonen, T., and Pihkala, T. (2020) Strategic renewal in a mature family-owned company – a resource role of the owners. *Long Range Planning*, **53**, 2, 101864.

Smart, P., Holmes, S., Lettice, F., Pitts, F.H., Zwiegelaar, J.B., Schwartz, G., and Evans, S. (2019) Open science and open innovation in a socio-political context: knowledge production for societal impact in an age of post-truth populism. *R&D Management*, **49**, 3, 279–297.

Song, M., van der Bij, H., and Weggeman, M. (2006) Factors for improving the level of knowledge generation in new product development. *R&D Management*, **36**, 2, 173–187.

Talke, K., Salomo, S., and Rost, K. (2010) How top management team diversity affects innovativeness and performance via the strategic choice to focus on innovation fields. *Research Policy*, **39**, 7, 907–918.

Tang, Y., Li, J., and Liu, Y. (2016) Does founder CEO status affect firm risk taking? *Journal of Leadership & Organizational Studies*, **23**, 3, 322–334.

Tebaldi, E. and Elmslie, B. (2013) Does institutional quality impact innovation? Evidence from cross-country patent grant data. *Applied Economics*, **45**, 7, 887–900.

Tomlinson, P.R. and Fai, F.M. (2016) The impact of deep vertical supply chain relationships upon focal-firm innovation performance. *R&D Management*, **46**, S1, 277–290.

Ucar, E. (2018) Local creative culture and corporate innovation. *Journal of Business Research*, **91**, 60–70.

Urban, G.L. and Von Hippel, E. (1988) Lead user analyses for the development of new industrial products. *Management Science*, **34**, 5, 569–582.

Uzzi, B. (1996) The sources and consequences of embeddedness for the economic performance of organizations: the network effect. *American Sociological Review*, **61**, 674–698.

Valentini, G. (2012) Measuring the effect of M&A on patenting quantity and quality. *Strategic Management Journal*, **33**, 3, 336–346.

Van de Wal, N., Boone, C., Gilsing, V., and Walrave, B. (2020) CEO research orientation, organizational context, and innovation in the pharmaceutical industry. *R&D Management*, **50**, 2, 239–254.

Velu, C. and Jacob, A. (2016) Business model innovation and owner–managers: the moderating role of competition. *R&D Management*, **46**, 3, 451–463.

Von Hippel, E., Franke, N., and Prügl, R. (2009) Pyramiding: efficient search for rare subjects. *Research Policy*, **38**, 9, 1397–1406.

Wang, C., Rodan, S., Fruin, M., and Xu, X. (2014) Knowledge networks, collaboration networks, and exploratory innovation. *Academy of Management Journal*, **57**, 2, 484–514.

Washington, M. and Zajac, E.J. (2005) Status evolution and competition: theory and evidence. *Academy of Management Journal*, **48**, 2, 282–296.

Welsh, R., Glenna, L., Lacy, W., and Biscotti, D. (2008) Close enough but not too far: assessing the effects of university–industry research relationships and the rise of academic capitalism. *Research Policy*, **37**, 10, 1854–1864.

Westphal, J.D. and Khanna, P. (2003) Keeping directors in line: social distancing as a control mechanism in the corporate elite. *Administrative Science Quarterly*, **48**, 3, 361–398.

Westphal, J.D. and Shani, G. (2016) Psyched-up to suck-up: self-regulated cognition, interpersonal influence, and recommendations for board appointments in the corporate elite. *Academy of Management Journal*, **59**, 2, 479–509.

Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wu, S., Levitas, E., and Priem, R.L. (2005) CEO tenure and company invention under differing levels of technological dynamism. *Academy of Management Journal*, **48**, 5, 859–873.

Xia, T. and Liu, X. (2022) The innovation paradox of TMT political capital in transition economy firms. *Journal of Business Research*, **142**, 775–790.

Xu, D., Zhou, K.Z., and Du, F. (2019) Deviant versus aspirational risk taking: the effects of performance feedback on bribery expenditure and R&D intensity. *Academy of Management Journal*, **62**, 4, 1226–1251.

Yan, B. and Luo, J. (2017) Measuring technological distance for patent mapping. *Journal of the Association for Information Science and Technology*, **68**, 2, 423–437.

Notes

1 We fully acknowledge that patents, as all proxies, are not perfect for capturing a firm's level of innovativeness. Indeed, they are mostly related to inventions, and some firms may opt for other forms to protect the latter, such as trade secrets. However, to date, patents still represent one of the most reliable and implemented ways to assess innovation (e.g., Lin and Chen, 2005; Rothaermel and Boeker, 2008; Tebaldi and Elmslie, 2013).

2 We are thankfully to an anonymous reviewer for highlighting this issue.

3 Results are robust to alternative operationalization of firm size as logarithm of firm's total assets.

4 We used 10 years of pre-sample patent data (1994–2004). This time span is in line with prior research (Li et al., 2019; Runge et al., 2022).

5 Considering the log transformation of the dependent variable: $\log(1+y)=x\ \mu+\alpha$, Cohn et al. (2022) show in Takeaway 4 that the relation between the semi-elasticities of $(1+y)$ and y is $\mu_j = \frac{E[y|x]}{1+E[y|x]}\beta_j$, when $E[y|x]$ is large, $\mu_j \approx \beta_j$, and the log transformed regression coefficient can be interpreted as an approximation of the semi-elasticity of y with respect to the x_j.

6 We ran separate panel-fixed-effect regressions for Hypothesis 2 and 3 (originally estimated by sureg). We still find similar results consistent with our hypotheses in two separate panel-fixed-effect models (the coefficient on the social status of TMTs for market value was $b=0.1$ with $p<0.05$; and the same coefficient for scientific value was $b=0.06$ with $p=0.15$, insignificant).

7 In the results presented in Table 9, we created a dummy variable taking zero if TMT social status is less than the third quartile (this is robust to several other splits), and one otherwise. This is the dichotomized TMT social status variable that is used as the dependent variable in the first stage of Heckman.

8 The treatment in this procedure was dichotomized TMT social status.

9 Network size is obtained by calculating "the number of overlaps through employment, other activities, and education" (WRDS BoardEx dictionary).

10 The same holds when we use panel Poisson with random effects.

11 We are thankful to an anonymous reviewer for suggesting this idea.

Ali Radfard is Lecturer of Strategy at Aston Business School (UK). He investigates the connections between corporate governance and social construction and the role of social construction of time in shaping the strategic decision-making. He has earned a PhD from Bocconi University. His PhD dissertation has been finalist for Pondy's Best Dissertation Paper Award at the OMT division of The Academy of Management in 2018. Ali has been a visiting researcher at the Ross School of Business in The University of Michigan (US).

Luca Pistilli is a Quinn School of Business Assistant Professor in Strategy and International Business. Luca obtained his PhD in Business Administration & Management from Bocconi University, defending a dissertation that granted him invitations to various conferences and events, among these the prestigious Consortium on Competitiveness and Cooperation 2018, held at Haas School of Business, University of California Berkeley, CA, USA. Luca has also held a visiting researcher position at Tuck School of Business at Dartmouth College, NH, USA. Luca's research focuses on organizational adaptation, Business Ethics, and entrepreneurial failure. Course taught and directed include Technology Innovation Strategy, Entrepreneurship, Innovation, and Corporate Social Responsibility.

Alessia Paccagnini is a tenured Assistant Professor at the University College Dublin School of Business. Previously, she was Lecturer at the School of Economics at the University College Dublin, Assistant Professor at the University of Milan – Bicocca, and Max Weber Fellow at the European University Institute. She earned her PhD in Economics and Econometrics from Bocconi University. During her career, she has been a research visitor at the European Central Bank, University of Pennsylvania, Universitat Pompeu Fabra, Bank of England, National Bank of Poland, and Visiting Professor at IMT Lucca and Universitat Autonoma de Barcelona. Her research includes Time Series Analysis, Forecasting, Factor Models, Classical and Bayesian Econometrics, Applied Macroeconomics, DSGE Model Estimation, and Monetary Policy. Her work has been published in internationally prestigious journals such as *Journal of Econometrics*, *Journal of Money, Credit and Banking*, *Macroeconomic Dynamics*, *Computational Statistics and Data Analysis*, *Economics Letters*, *International Journal of Forecasting*, *Journal of Empirical Finance*, *Journal of Economic Dynamics, and Control*, and *Journal of Financial Stability* among others. Alessia is among the top 5% female economists and the top 8% economists all around the world considering the last 10 years of publications.

