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REWARDS FOR PATENTS AND INVENTOR BEHAVIORS IN INDUSTRIAL RESEARCH AND DEVELOPMENT

MARCO S. GIARRATANA
IE University

MYRIAM MARIANI
Bocconi University

INGO WELLER
LMU Munich

This study investigates the effects of rewards in a research and development (R&D) setting in which employees' inventive efforts lead to patented inventions. Pay for performance (PFP) for inventions is associated with two challenges: Low-quality inventions may be rewarded (false positives), and high-quality inventions may be overlooked (false negatives). Building on previous findings regarding the motivational and informational effects of rewards, we use social identity theory to predict that different types of inventors react differently to such false positive and false negative information. Specifically, we hypothesize that PFP that produces false positives has detrimental effects on corporate inventors with a taste for science, who are motivated by scientific prestige, reputation, and intellectual curiosity. The empirical results from survey data related to 3,995 inventor–patent pairs show that, for this particular group of inventors, false positives are associated with reduced effort in research activities and fewer interactions with peers in the R&D department. In addition, these effects are stronger when firms have many patents and thus provide less noisy information to corporate inventors.

Pay for performance (PFP) is a prevalent human resource management (HRM) practice (Rynes, Gerhart, & Parks, 2005), spreading across diverse sectors, including those that traditionally have preferred fixed compensation, such as education, health, and innovation (CEB, 2006; Gerhart, Rynes, & Fulmer, 2009). Empirical evidence suggests that PFP enhances individual-level performance and organizational success (Gerhart et al., 2009), yet it remains a complex topic, marked by disagreement about the contexts in which PFP is most effective, for whom, and in what conditions (Larkin, Pierce, & Gino, 2012; Nyberg, Pieper, & Trevor, 2016).

One critical finding indicates that PFP is most effective when pay is closely tied to performance (Trevor, Reilly, & Gerhart, 2012). However, even if firms intend to tie pay to performance, they may not be able to do so. For example, performance cannot always be observed or measured objectively, and subjective performance measures also have drawbacks, such as the threat of rater biases (Kampkötter & Sliwka, 2016; Rynes et al., 2005). Furthermore, firms might strategically prefer to decouple pay from performance, such as when they run contests with fewer prizes compared to competitors (e.g., Bothner, Podolny, & Smith, 2011; Boudreau, Lacetera, & Lakhani, 2011; Lazear & Rosen, 1981) or use excessive rewards to stimulate risky behaviors (Baumann & Stieglitz, 2014; Ederer & Manso, 2013; Scherer & Harhoff, 2000).

When pay and performance are not in sync, two types of false rewards occur: Low-performance

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contributions may be rewarded, and high-performance contributions may be overlooked. The first issue represents "false positive" rewards; the second indicates "false negative" rewards.[1] Substantial literature has described the nature of performance appraisals and the use and effects of PFP, but the implications of the dual nature of false rewards are not well understood. Some theories in related fields, like the economics of law and crime, have investigated the differential deterrence effects of judicial systems that commit Type I errors (i.e., convicting innocent people) or Type II errors (i.e., failing to convict those who are guilty) (Rizzolli & Stanca, 2012). Gamba and Stanca (2016) modeled a bidding contest and varied inclusion and exclusion errors; Marchegiani, Reggiani, and Rizzolli (2016) analyzed whether failing to reward a deserving agent is more detrimental than rewarding an undeserving agent.

We apply these notions to innovation contexts by exploiting field data related to innovation and patenting. We analyze how PFP for patents creates false positives and false negatives, and how these false rewards differ in their impact on employee behaviors. Using social identity theory (Ashforth & Mael, 1989; Tajfel & Turner, 1986), we develop predictions about the different information provided by false positives and false negatives. False positives collide with the beliefs and norms of corporate scientists—that is, inventors who work for for-profit firms but who embrace a traditional view in which scientists are driven by a desire to resolve challenges and gain recognition from their peer community (Gustin, 1973; Merton, 1973; Roach & Sauermann, 2010; Stern, 2004). These corporate scientists identify with the scientific "guild" and its beliefs, rules, and norms, which include winner-take-all reward structures (Mudambi & Swift, 2009; Stephan, 1996). Therefore, corporate scientists should react negatively to PFP that produces many false positives, because this system threatens their belief and value structures, as well as their social identity as scientists. In line with this contention, we observe that false positives lead corporate scientists to reduce the effort they devote to research and development (R&D) and the extent to which they interact with R&D peers. We also find that these results are stronger in firms with many patents that provide corporate inventors with more precise information about the company reward system. False negatives, instead, do not show any significant association with these inventors' behaviors.

As its main contribution, our work extends the informational perspective of PFP (Gerhart et al., 2009; Lazear, 2000; Shaw, 2015) by accounting for the dual nature of false rewards. Specifically, we amend traditional (agency) perspectives with social identity arguments (Ashforth & Mael, 1989; Tajfel & Turner, 1986). Whereas agency theory predicts equally negative effects of both types of false rewards (Gamba & Stanca, 2016; Marchegiani et al., 2016), we anticipate that false positives are tangible artifacts and symbols that conflict with collective, behaviorally relevant belief systems and norms.

Furthermore, we add to growing literature on the "interplay between a firm's motivational system and its employees' mix of motives" (Bridoux, Coeurderoy, & Durand, 2011: 712). The match (or mismatch) between individual preferences and pay attributes can produce relevant and differential effects of PFP strategies, leading to a significant source of interfirm heterogeneity (Chng, Rodgers, Shih, & Song, 2012; Larkin et al., 2012; Wowak & Hambrick, 2010). We introduce individual-level heterogeneity as a social identity- or group-based phenomenon. Employees identify with social groups ("invisible colleges" [Gustin, 1973]) within their firms and develop shared norms and beliefs (Tajfel & Turner, 1986), which interact positively or negatively with the firm's policies and practices, such as pay systems.

THEORY DEVELOPMENT

Background Literature

This research relates to several different strands of literature, including PFP and performance appraisal, contest, and innovation research. These broad research fields embrace multiple disciplines (e.g., management, innovation, economics, psychology), but our review focuses on those studies that relate most consistently and closely to our research question and setting. That is, we focus on prior work that aims to explain how false rewards arise and that links false rewards to individual-level behaviors. Moreover, because we explore individual-level behaviors rather than collective outcomes (e.g., social welfare [Bothner

[1] These two issues also have been termed inclusion/exclusion errors (Gamba & Stanca, 2016) or Type I/Type II errors (Marchegiani, Reggiani, & Rizzolli, 2016), with some distinct definitions (Markussen, Putterman, & Tyran, 2014). We use the terms "false positives" and "false negatives" to highlight that pay and performance are not in sync, while avoiding overstressing the error connotation.

et al., 2011]), we concentrate on studies that deal with individual-level factors and explanations.

PFP and performance appraisal literature. A lively debate about the effectiveness of PFP for achieving desired employee behaviors spans both academic research (Nyberg et al., 2016) and the popular press (e.g., Pink, 2009). Even PFP advocates conclude that when it "works, it seems capable of producing spectacularly good results and when it does not work, it can likewise produce spectacularly bad results" (Gerhart et al., 2009: 253). An informative theme in PFP research relates to pay dispersion (Shaw, 2014, 2015; Trevor et al., 2012). This line of research notes that dispersion in explained pay, or the proportion of an employee's pay that "is tied to productivity-relevant employee inputs" (Trevor et al., 2012: 586), predicts performance better than does dispersion in unexplained pay, which stems from other sources, such as seniority-based recognition, "politics, discrimination, favoritism, [or] random decisions" (Trevor et al., 2012: 586). These latter processes, which are unrelated to employees' performance, subvert expectations of procedural justice (Lind & Tyler, 1988; Thibaut & Walker, 1975) and result in inequitable input–output relations, thus violating distributional fairness rules (Adams, 1963; Trevor et al., 2012). According to equity theory (Adams, 1963), people who receive inequitable treatment vary or cognitively adjust their inputs or outputs, manipulate others' inputs or outputs, withdraw, or change their reference group. In addition, relative underpayment (which is correlated with the risk of false negatives) and relative overpayment (which is correlated with the risk of false positives) result in different reactions. Research has indicated that equity predictions are better supported in the context of underpayment than overpayment (Pritchard, 1969).

The concepts of explained and unexplained pay also relate to performance appraisal literature (Landy & Farr, 1983; Murphy & Cleveland, 1995; Rynes et al., 2005). Performance appraisals may be subjective or based on objective output measures. With subjective appraisals, raters often exhibit severity, leniency, or centrality biases (Landy & Farr, 1983; Marchegiani et al., 2016; Murphy & Cleveland, 1995), and ratings tend to be unreliable (Viswesvaran, Ones, & Schmidt, 1996). Objective measures, such as productivity or sales volume (Rynes et al., 2005), can remedy such concerns but are seldom available, or they might be available only at aggregate, instead of individual, levels. Moreover, objective measures tend to be narrow in scope, whereas desired employee behaviors are broader, such that multitasking trade-offs almost inevitably arise (Lawler, 1971; Manthei & Sliwka, 2013; Rynes et al., 2005).

Problems and biases in performance appraisals lead to false rewards and weaken the incentive effect of PFP tied to these appraisals. Extant contributions have argued that both false positives and false negatives "should be equally detrimental to the agent's effort provision" (Marchegiani et al., 2016: 184), because for risk-neutral agents "exclusion and inclusion [errors] have the same negative impact on effort, as they reduce its marginal return by the same amount" (Gamba & Stanca, 2016: 2).

Strategic HRM, contest design, and innovation literature. Strategic HRM literature has recognized that PFP is a crucial driver of firm performance and integral to high-performance work systems (Huselid, 1995; Posthuma, Campion, Masimova, & Campion, 2013). Two types of PFP systems generate false rewards: nontrivial contests that generate false negatives, and excessive reward strategies that produce false positives. First, nontrivial contests create a competitive situation with fewer rewards than competitors; at the extreme, "winner-take-all markets translate small differences in performance into large differences in reward" (Frank & Cook, 1996: 29). Such selective rewards can have more positive performance effects compared to broadly distributed rewards (Bradler, Dur, Neckermann, & Non, 2016).

Second, some firms allocate rewards to low-performance outcomes (i.e., false positives), as in the case of "golden parachutes" that help establish more tolerance for failure and encourage a risk-taking culture (Ederer & Manso, 2013). Rewarding more outcomes than a few, highly ranked ones is common in creative and innovative contexts, in which the performance distribution is skewed (Fleming, 2007). This observation holds for patented inventions, whose value distribution is typically log-normal with a stretched right tail (Giuri et al., 2007; Hall, Jaffe, & Trajtenberg, 2005; Scherer & Harhoff, 2000; Silverberg & Verspagen, 2007; Trajtenberg, 1990). That is, the top 10% of patents often account for more than 80% of the market value of all patents (Scherer, Harhoff, & Kukies, 2000).

Inventing may also be related to false negatives. Innovation, from "the germ of an idea to its impact on society" (Garud, Tuertscher, & Van de Ven, 2013: 776), confronts manifold technological and market risks (Christensen, 1997; Giarratana & Mariani, 2014). Inventions are often poorly defined at the outset, and their success or failure manifests long after their generation and entry into the market (Gambardella, Giarratana, & Panico, 2010). For example, 90% of all pharmaceutical R&D investments go to drugs that ultimately fail (*The Economist*, 2014). Thus, creative forecasting (i.e., predicting the outcomes of new ideas [Berg, 2016]) is per se uncertain and can result in both false positives and false negatives.

Innovation, Patenting, and False Rewards

Firms employ a broad set of rewards to honor innovative efforts. In addition to salaries, which are the largest, most often used pay component for inventors, firms offer incentives, including bonuses for patents, royalty compensation plans (CEB, 2006; Malanowski, 2007), increased autonomy that allows employees to organize their time and research activities, the option to publish research results, or research grants (Gustin, 1973; Stern, 2004). In general, PFP for patents is widespread, with more than three-quarters of U.S. firms using it (CEB, 2006). The extent to which firms use PFP for patents differs across countries and institutional settings, as well as among firms in the same country (Harhoff & Hoisl, 2007).

When rewarding inventors, firms primarily seek to calibrate the rewards according to the likely value of the invention (Harhoff & Hoisl, 2007). This logic, which we refer to as "value-based PFP," is similar to explained pay (Shaw, 2014; Trevor et al., 2012). Value-based PFP starts with creative forecasting (Berg, 2016): Building on their past experience, analyst evaluations, and industry benchmarks, firms gather knowledge to predict the expected value of their inventions. However, given the uncertainty of the invention process, they naturally struggle with predictions about the potential of any invention to fall into the right tail of the value distribution.

As both a challenge and an opportunity, the invention process has multiple steps, carried out by different actors, so roles and responsibilities are divided: "creators are expected to generate novel and useful ideas (variation), managers decide which of these ideas to implement (selection), and the external audience determines the ultimate success of any implemented ideas (retention)" (Berg, 2016: 435). On the one hand, split roles and responsibilities create informational problems, opportunities for politics, and threats of favoritism, which make it more difficult to anticipate the future value of an invention. On the other hand, multiple actors are also multiple information sources; peers in particular are knowledgeable informants (Berg, 2016; Bridoux et al., 2011). Most inventions result from teamwork (Harhoff & Hoisl, 2007), and inventors often engage in multiple projects with varying team compositions, so they can gain insights into multiple contributions, which should improve their potential to understand and assess the invention process and its outcomes. Predictive abilities may also benefit from path-dependent projects or from consistency, such that star researchers consistently produce high-quality inventions (Call, Nyberg, & Thatcher, 2015).

Although the expected value of an invention is the most important PFP criterion, firms' reward strategies may respond to other rationales as well. For example, managers may be tempted to use politics and power (Pfeffer, 1992). Due to resource constraints that limit the number of proposed projects that can be implemented (Foss, 2003), firms might attempt to limit bonus payments, worried that too many incentives will produce excess ideas that cannot be funded (Baumann & Stieglitz, 2014). Other companies might reward a vast number of patents in an effort to stimulate risky behaviors, establish tolerance for failure (Ederer & Manso, 2013), or build large patent portfolios that can deter competitors (Ziedonis, 2004).

Overall, then, PFP for patents comprises two components, and the weight attached to each component varies across time and firms. The first component reflects a value-based logic, such that firms engage in creative forecasting and try to reward the most promising inventions. The second component is based on reasons unrelated to performance. To illustrate the functioning of PFP in such a setting, consider a simple simulation. Assume a population of patents, in which the proportions of high-quality (15%) and low-quality (85%) patents are fixed. These proportions are realistic (Scherer et al., 2000; *The Economist*, 2014). Next, imagine four reward regimes:

(1) random selection, such that firms are unable to predict the future value of the inventions and draw from a uniform distribution,
(2) perfect selection, according to which firms have perfect knowledge about the future value of inventions and reward them accordingly,
(3) informed selection, such that high-quality patents have a higher probability of being rewarded compared to low-quality patents (e.g., twice as likely), and
(4) twofold selection, in which 50% of rewards are assigned to high-quality patents (perfect selection) and 50% of rewards go to all remaining patents.

If we simulate these regimes with different proportions of rewarded patents (see Appendix A), random selection produces a linear process, and false positives and false negatives develop symmetrically but in opposite directions. With perfect selection, the percentage of false positives increases steeply after all high-quality patents have been rewarded. Informed selection mixes these two outcomes, and twofold selection creates an asymmetric process, in which further increases in reward breadth produce relatively larger increases in false positives than decreases in false negatives. The twofold selection outcome fits our empirical data well: As we explain subsequently, as the ratio of rewarded to unrewarded patents increases, false positives increase more strongly than false negatives decrease. Therefore, we use this selection model as the starting point for developing theory about inventors' reactions to false rewards.

PFP, Individual Differences, and Social Identification

As Wowak and Hambrick (2010: 804) explained, "pay cannot be studied in isolation;" rather, pay effects likely vary with individual differences (Barrick, Mount, & Li, 2013; Bartling, Fehr, & Schmidt, 2012; Bridoux et al., 2011; Chng et al., 2012; Larkin et al., 2012; Prasad, Enns, & Ferratt, 2007; Wowak & Hambrick, 2010). In general, researchers are a fairly heterogeneous group of knowledge workers (Roach & Sauermann, 2010). Those with a "taste for science" (Gustin, 1973; Merton, 1973) value the freedom to choose projects, enjoy opportunities to publish their research results, present their achievements to peers, and strive for their peer community's recognition (Merton, 1973; Roach & Sauermann, 2010; Stern, 2004). Above all, "the scientist is reminded that it is his role to advance knowledge" (Merton, 1973: 293), and a reward "often attributed to science is the satisfaction derived from solving the puzzle" (Stephan, 1996: 1203). Moreover, owing to the primacy principle—"a key component of the scientific guild's measures of excellence" (Mudambi & Swift, 2009: 738)—a winner-take-all logic is pervasive in science (Stephan, 1996).

Relative to other inventors in industrial R&D, corporate researchers with a taste for science are more similar to scientists in academia (Sauermann & Cohen, 2010; Sauermann & Stephan, 2013). Stephan (1996: 1209–1210) highlighted that "the research of some scientists and engineers in companies like IBM, AT&T, and Du Pont is virtually indistinguishable from that of their academic counterparts" and that "Bell Labs, Du Pont, IBM, Smith Kline and French, Sony, and General Electric have each been the research home to scientists who have subsequently won the Nobel Prize" (see Arora, Belenzon, & Patacconi, 2015). We label the group of industrial inventors with a taste for science as "corporate scientists."

The strong prestige of science as a field (Chalmers, 1999; Stephan, 1996), together with the salient and distinctive norms maintained by the "scientific guild" (Mudambi & Swift, 2009), enable scientists to form a strong collective identity that spans both corporate and academic worlds. To frame and understand this social group formation process, we turn to social identity theory (Ashforth & Mael, 1989; Tajfel & Turner, 1986), which posits that people exhibit a fundamental need to maintain and improve their self-concepts (Epstein, 1998). They therefore sort themselves and others into social categories (Tajfel, 1981) and units like "fathers," "friends," "athletes," "scientists," or more generally "group members." This social classification has two main functions: cognitive segmentation, related to shared or group mental models (Cannon-Bowers, Salas, & Converse, 1993; Klimoski & Mohammed, 1994), and social identification, in the sense of "oneness with or belongingness to some human aggregate" (Ashforth & Mael, 1989: 21). Work settings and organizations are important reference objects (Ashforth & Mael, 1989) because they provide multiple opportunities for feedback, from both social (e.g., peers) and administrative (e.g., pay systems) sources (Leonard, Beauvais, & Scholl, 1999).

Social identification theory postulates (Tajfel & Turner, 1986) that a person forms a sense of self through three crucial steps: categorization, or the selection of a reference group; identification, which entails adoption of the reference group's values and beliefs; and comparison, such that symbols and behaviors distinguish in-group from out-group members. The simultaneous occurrence of the three steps produces an augmented individual identity that can generate reciprocal behaviors (Tajfel & Turner, 1986) and positive attitudes such as commitment or empowerment (Settoon, Bennett, & Liden, 1996). In this sense, corporate scientists identify with the scientific community's values about rewards and reward structures: In science, there are "no awards for being second or third;" rather, a reward is "priority-based and reflects the value of the winner's contribution to science" (Stephan, 1996: 1202).

Social Identification and Information from Rewards

PFP initiates both motivational and informational processes. First, pay is intended to motivate employees to exert more effort. Second, pay practices have informational (also called signaling or sorting) effects (Gerhart et al., 2009; Lazear, 2000; Shaw, 2015), which mitigate information asymmetries in imperfect markets (Connelly, Certo, Ireland, & Reutzel, 2011; Spence, 1973). Through PFP, employees receive information and attach subjective meanings to the pay system of their firm—though these meanings may differ from the firm's actual intentions (Bowen & Ostroff, 2004; Liao, Toya, Lepak, & Hong, 2009; Nishii, Lepak, & Schneider, 2008). Our theory follows directly from these processes, with the arguments that rewards and false rewards both have motivational and informational effects, and that false rewards get interpreted differently by scientists and nonscientists.

From a motivational perspective, rewards have positive effects on effort and performance because they reinforce desired behaviors, reflect equitable input–output relations (Adams, 1963), and increase the instrumentality of efforts (Vroom, 1964). They also inform employees about the firm's desired behaviors, as well as its strategic intentions. For example, firms may want to establish a culture that tolerates failure (Ederer & Manso, 2013), and rewards for risky outcomes would signal this approach. Rewards are also tangible artifacts that result from selection and appraisal processes. Thereby, they establish social group boundaries (e.g., high versus low performers, those to retain or fire) and evoke social comparison processes (Ockenfels, Sliwka, & Werner, 2015), which are necessary for social classification and identity formation.

False rewards also have motivational and informational effects. False positives lower the opportunity costs of decreasing effort, and false negatives lower the instrumentality of rewards. From a motivational perspective, though, it is hard to determine whether one type of false reward might exert a stronger negative effect than the other. From an informational perspective, false rewards provide helpful information about the firm's type, such as whether it is more scientific or commercial (Murray, 2010). False positives, in particular, provide strong and tangible feedback that the firm tolerates failure and appreciates risk. However, they also signal a conflict with the values of the scientific community that only rewards stellar performance. As such, false positives potentially generate discontent because they violate an important norm. Such norm violations and their effects have been vividly documented (Murray, 2010): When Harvard researchers patented the "Oncomouse," a genetically manipulated mouse with a predisposition to cancer, and licensed it to DuPont, scientists were frustrated over the commercial use of their invention. As a result, they began to reinterpret the meaning of patents and "incorporated them into hybrid exchanges at the boundary as a means of maintaining (and even strengthening) the distinction between the academic and commercial logics" (Murray, 2010: 346).[2] False negatives instead are inevitably noisy signals, because it is difficult to interpret whether they result from uncertainty or strategic considerations.

Hypotheses

False positives lower individual effort by reducing the opportunity costs of diminished effort, for corporate scientists and nonscientists alike. Organizations that reward many patents (and thus generate false positives) indicate that they are using these rewards for purposes other than to recognize outstanding achievements. Such uses might lead to negative social comparisons and envy (Nickerson & Zenger, 2008), harm morale, stimulate unethical behavior, and lower effort (Larkin et al., 2012), as well as resulting in perceptions of relative deprivation (Crosby, 1984; Walker & Pettigrew, 1984) and unfairness (Greenberg & Colquitt, 2005). Such outcomes are detrimental to both the social climate at work (Collins & Smith, 2006) and employees' creative output. Harhoff and Hoisl (2007) found that such work conflicts represent a major perceived drawback of competitive pay schemes in an innovation context.

Unlike false negatives, which may remain unnoticed, false positives are tangible and create symbolic power. They also carry important information about the firm's type and strategic intentions, which may affect corporate scientists more strongly than nonscientists. Corporate scientists find it difficult to reinforce their self-concept when rewards are omnipresent. In response, they may choose to change "the out-group with which the in-group is compared" (Ashforth & Mael, 1989: 24), withdraw from

[2] As a second example, researchers in academia may receive rewards from their institutions for publishing articles in scientific journals. The journals' review processes and decisions reveal the researchers' contributions, outcomes, and rewards, which may be perceived as correct, false positives, or false negatives. Rewards for publications also carry a symbolic meaning that distinguishes academic scientists from other faculty members. If many systematic false positives occur, the value of rewards for publications diminishes and loses its identity formation function.

their peers in R&D, and collaborate with other members of their organization. In posing salient threats to the identities of corporate scientists, false positives cause them to perceive that they are relatively more deprived and unfairly treated compared to other inventors. Following social identity, equity, and withdrawal theory (Adams, 1963; Hulin, Roznowski, & Hachiya, 1985), we expect that in response to false positives, corporate scientists invest less in R&D tasks and turn to alternative reference groups within the firm.

Hypothesis 1. With increasing levels of false positives, corporate scientists (relative to other types of inventors) (a) dedicate fewer working hours to R&D tasks and (b) invest less in interactions with peers from the R&D department.

In contrast, false negatives are relatively noisy and difficult to interpret. They might reflect the uncertainty of the context, indicate that the firm uses rewards selectively, or both. Because selective rewards mimic the scientific reward structure and norms, corporate scientists (relative to nonscientists) should react less negatively, or even positively, to false negatives. At a minimum, because of the noise that accompanies false negatives, they should have a significantly weaker relationship with identity threats compared to false positives. We therefore hypothesize:

Hypothesis 2. The effects of false positives on corporate scientists' (a) working time in R&D tasks and (b) interactions with peers in R&D are more strongly negative than are the effects of false negatives.

Finally, false rewards may have stronger effects in firms that own many patents. To convey consistent messages, firms must establish a sufficiently large stream of observations and information that employees can interpret. According to signaling theory (Bangerter, Roulin, & König, 2012; Connelly et al., 2011), clear signals are observable and intense, and occur frequently. Connelly et al. (2011: 53–54) noted that sending information "repetitively can increase the effectiveness of the signaling process." In firms with only a few inventions and patents, PFP and false rewards are difficult to interpret, but in firms with many inventions and patents, false rewards emerge as a consistent pattern. Similarly, strategic HRM literature has recognized that firms can create more uniform and unambiguous reactions among employees if they implement strong, distinctive, and consistent HRM systems (Bowen & Ostroff, 2004). Firms that have many patents create consistency by "establishing an effect over time and modalities whereby the effect occurs each time the entity is present" (Bowen & Ostroff, 2004: 201). In summary, observations of reward decisions about many patents reveal false rewards as a consistent pattern, which facilitates employees' sense-making process and creates stronger feedback effects. We posit:

Hypothesis 3. The effects of false positives on corporate scientists' (a) working time in R&D tasks and (b) interactions with peers in R&D are more strongly negative when the firm has many patents.

DATA AND MEASURES

Sample Description

Our data come from a survey conducted between 2009 and 2011 in 20 European countries, Israel, the United States, and Japan among inventors who applied for a patent to the European Patent Office, with priority dates between 2003 and 2005. Appendix B provides a detailed description. From the 22,557 valid responses to this survey, we extract a sample that matches our theoretical requirements. We first select patents owned by for-profit corporations (77% of all observations). We then focus on inventors who work in formal R&D projects and whose regular job is "inventing" in an R&D department (50% of observations). In addition, we only consider firms with two or more patents in the database (73% of observations) to reduce the potential noise due to sporadic innovators. After excluding cases with missing data for our core covariates, the final sample consists of 3,955 patent–inventor observations.[3]

Dependent Variables

The dependent variables measure inventors' behaviors during projects that led to a patented invention. We use responses to two survey questions. The first question, *R&D Working Hours*, reflects the number of weekly working hours that the inventor dedicated to creative R&D activities. The second

[3] Hoisl and Mariani (2016) and Torrisi et al. (2016) used data from this same survey. Their studies addressed different issues (i.e., gender pay gap; use and nonuse of patents) and employed different dependent variables. Most of the control variables differed too, with only some similarity in the basic inventor- and firm-level control indicators. They also employed different subsets of the overall sample.

question pertains to the relative frequency of communication and interactions with colleagues in the R&D department. We construct *Interactions with R&D Colleagues* as $(a - b)/(a + b)$, where a is the frequency of interactions with colleagues in the R&D department, and b is the average frequency of interactions with colleagues in other departments (production, marketing, logistics, human resources). The scales for both a and b range from 1 ("never") to 5 ("daily").

Corporate Scientists

To differentiate corporate scientists from other inventors, we focus on two main work motivations of scientists, as suggested in sociological literature (Gustin, 1973; Merton, 1973): peer community recognition and a desire to solve intellectual challenges. The inventors assessed their motivations on five-point rating scales, ranging from 1 = "not important" to 5 = "very important." From their responses, we created a dummy variable (*Corporate Scientists*) that takes a value of 1 for all inventors who rated both recognition and intellectual challenges higher than the sample median (2 and 3, respectively). A dummy variable approach can identify inventors who score high on both dimensions (Prendergast, 2008) and is conceptually aligned with our theory of social identity formation and social group membership, in that it clearly demarcates corporate scientists from other types of inventors.[4]

Our data reveal some salient characteristics of corporate scientists. On average, they publish 10.7 scientific articles, compared with 6.74 by other inventors; 35% hold a PhD, versus 25% of other inventors. These differences are statistically significant at the 1% level. Table 1 shows that corporate scientists account for 17.4% of the sample. As we demonstrate subsequently, these motivations are also stable over time.

False Positives and False Negatives

To measure false positives and false negatives, we use two survey questions. First, we gather information about whether the inventor, as a result of the focal invention, received a permanent salary increase (2.2%), a one-shot bonus (54.5%), a payment conditional on future revenues from the patent (16%), career advancement opportunities (4.7%), or none of these rewards (22.6%). In line with our theory, we define salary increases or bonus payments as PFP rewards that accrue when a patent is filed.[5]

Second, the inventors provided an estimate of the monetary value of the patented invention, based on their expert experience and knowledge they had accumulated between the filing date and the time of the survey.[6] This self-reported patent value indicator was cross-validated with a regression approach in which the indicator served as the dependent variable, and standard proxies for patent value (e.g., forward citations, patent claims, number of patents in the patent family [Trajtenberg, 1990]) were the independent variables. The results from these estimations (available on request) confirm that the covariates are highly correlated with self-reported patent value, after controlling for several other sources of patent value heterogeneity.

Third, we compare the monetary value of the focal patent with the average monetary value of all patents in the same technological class in our survey.[7] Then, *False Positives* is the number of a firm's rewarded patents whose value is below the average value of patents in the same technological class, divided by

[4] Our results also hold if we employ the sample mean (more than 3 and 4, respectively) to define the threshold, and if we define corporate scientists by applying a clustering procedure to the two motivations (i.e., using the city block distance metric and centroids equal to the medians). Similarly, in the upcoming regressions, the estimated results show the same signs (but slightly lower statistical significance thresholds) when we use the sum of the motivation scores as a continuous variable.

[5] In alternative specifications (available on request), we treated other payments conditional on future patent revenues and career advancement opportunities as PFP components. Alternatively, we controlled for them in the regressions. The estimated results do not change relative to those that use only monetary rewards at the time of the invention.

[6] Specifically, the survey asked: "Suppose that on the day in which this patent was applied for, the applicant and you had all the information you have today regarding the value of this and the related patents. In case a potential competitor of the applicant was interested in buying the whole set of patents (the patent family including all national patents derived from it), what would have been the minimum price (in euros) that the applicant should have demanded?" The respondents were provided with 10 value classes, from 0 to more than 300 million euros.

[7] Patents were classified into 30 ISI-INPI-OST technological classes (http://www.wipo.int/export/sites/ www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf). The results did not substantially change when we used the average value of all patents in all technological classes for a focal firm.

TABLE 1
Corporate Inventors and Motivations to Invent

		Intellectual Challenge		
		Below the Median (%)	**Above the Median (%)**	**Total (%)**
Scientific Reputation	Below the Median	46.4	23.8	70.2
	Above the Median	12.4	17.4	29.8
	Total	58.8	41.2	100.0

Notes: 3,955 observations.

all of a firm's patents. Following the same logic, *False Negatives* is the number of a firm's nonrewarded patents whose value is above the average value of patents in the same technological class, over all of a firm's patents.[8] Note that *False Positives* and *False Negatives* are firm-level variables that reflect the firms' pay system and the degree to which it is affected by false rewards. *Rewarded Patents* is the overall share of a firm's patents that the firm rewarded with a bonus.

Table 2 shows that the average share of *Rewarded Patents* is 41%, and about half of them have a value below the sample average (*False Positives*), whereas only 7% achieve a value above the sample average but do not receive a monetary reward (*False Negatives*). The correlation between *Rewarded Patents* and *False Positives* is strong and positive; the correlation between *Rewarded Patents* and *False Negatives* is negative, as expected. Thus, in line with the twofold selection regime explained in Appendix A, the larger the share of rewarded patents, the greater the probability that both low- and high-value patents receive a reward.

Table 3 contains the results of a *t*-test that compares *False Negatives* and *False Positives* in firms with a different reward breadth; that is, for firms where *Rewarded Patents* is either above or below the sample median. This comparison again confirms the expected trade-off: With more *Rewarded Patents*, *False Negatives* are relatively lower, and *False Positives* are relatively higher. However, the increase in *False Positives* is much larger than the decrease in *False Negatives* (the absolute difference between the *False Positives* estimates is about four times greater than that of *False Negatives*).

We also estimate ordinary least squares (OLS) regressions at the firm level that employ *False Positives* and *False Negatives* as dependent variables, with *Rewarded Patents* as the key independent variable, as well as the control variables detailed in the next section. These estimated results (available on request) show that *Rewarded Patents* correlate negatively with *False Negatives* ($\beta = -0.112$, $SE = 0.014$) and positively with *False Positives* ($\beta = 0.473$, $SE = 0.022$), in line with the simulation patterns that we present in Appendix A.

Control Variables

We control for several sources of heterogeneity at different levels: patent, inventor, and firm. An inventor's work autonomy could influence her or his ability to choose the level of *R&D Working Hours*, as well as the degree of her or his *Interactions with R&D Colleagues*. Thus, the first factor that we control for is *Autonomy*, defined as an inventor's ability to allocate his or her working time freely to different tasks or projects. We measure this variable on a scale from 1 ("very low") to 5 ("very high").

In addition to information about whether a patent received a bonus, we have some details (but with

TABLE 2
Rewarded Patents, False Positives, and False Negatives

			Correlations		
Variables	**Mean**	***SD***	**1**	**2**	**3**
1. *Rewarded Patents*	0.41	0.24	1		
2. *False Negatives*	0.07	0.09	−0.31***	1	
3. *False Positives*	0.19	0.15	0.73***	−0.23***	1

Notes: 3,955 observations. The statistics were derived from individual-level patent observations. Firm-level statistics are virtually identical and available on request.
***$p < .01$

[8] We performed robustness checks with different cutoff points to define *False Positives* and *False Negatives*, including the median and the 55th, 60th, and 75th percentiles of the patent value distribution. The signs and statistical significances of the estimated results (available on request) were consistently confirmed; the magnitude of the coefficients decreased for higher cutoff values, though, probably due to range restrictions.

TABLE 3
False Positives and False Negatives: Firm Comparisons

	% False Negatives	*% False Positives*
Firms with *Rewarded Patents* below the median	0.096 (0.002)	0.096 (0.001)
Firms with *Rewarded Patents* above the median	0.046 (0.001)	0.285 (0.002)
Difference (*t*-test; *p* value)	0.05*** (0.002)	−0.189*** (0.00)

Notes: 3,955 observations. The statistics were derived from individual-level patent observations. Firm-level statistics are virtually identical and available on request.
***$p < .01$

sizable missing data) about the size of the bonus (i.e., monetary value of the reward). We aggregate the reward size data to the firm level and use the standard deviation to control for the dispersion of reward size within a firm.[9] Information about pay systems can be weak or strong, depending on the frequency with which it is transmitted and the similarity of the rewards. For example, the expected negative effect of *False Positives* could be mitigated if companies used heterogeneous reward intensities to discriminate between low- and high-quality patents. The *Reward Size Standard Deviation* variable, which measures within-firm standard deviations in reward size, controls for such effects.

As additional scientist-level controls, we use the number of weekly working hours (*Working Hours*), annual income (*Income*), gender (*Gender* dummy: 1 = men, 0 = women), years of experience as an inventor (*Experience*), education (*PhD* and *Bachelor's or Master's* dummies, with high school or lower degrees as the baseline), stock of past inventions (*Inventor's Past Inventions*), and stock of past publications (*Inventor's Past Publications*). We also control for project-specific factors that could correlate with inventor behaviors, such as whether the patent is the result of teamwork (*Teamwork* dummy), the size of the project investment in terms of the log of the number of man-months employed to develop the invention (*Project Size*), whether the patent is part of a patent family that composes the invention (*Patent Family* dummy), and whether the project is financed with the firm's internal cash (*Funding* dummy). At the firm level, we control for firm size (*Large Firm* indicates firms with more than 250 employees, *Medium Firm* is 50–250 employees; the reference group is smaller firms), the log of stock of the firm's patents in the survey (*Firm Patents*), R&D employees over total firm employees (*R&D Intensity*),[10] and the extent to which the firm provides a scientifically or technically stimulating work environment (*Work Environment*), measured on a 1–5 scale. Finally, we include dummies for patent priority years (*Year2003*, *Year2004,* and *Year2005*), the technological classes of the patents (30 technology class dummies), and the 23 countries of the inventors' residence. Table 4 displays the descriptive statistics; Appendix C lists the variables and their definitions.

RESULTS

Table 5 contains the results of four patent–inventor-level OLS regressions with robust standard errors clustered by firm, where the dependent variable is *R&D Working Hours*. Table 6 mirrors these regressions for the outcome variable *Interactions with R&D Colleagues*. In each set, we add the covariates stepwise to the models. The main effects of *False Positives* and *False Negatives* on the dependent variables are statistically not significant, but when we allow *False Positives* to interact with *Corporate Scientists*, the coefficient is negative and statistically significant ($p < .01$) for both *R&D Working Hours* and *Interactions with R&D Colleagues*. Thus, *Corporate Scientists* dedicate fewer working hours to R&D and withdraw from their closest peers in the R&D department

[9] The firm-level aggregation makes the missing-data problem less intense. We also conducted robustness checks in which we used the average monetary value of the reward at the company level, together with individual-level bonus and false rewards variables (i.e., patent received a reward/did not receive a reward and was/was not economically successful). In interviews with a small sample of inventors (detailed in the "Evidence from Interviews" section), we confirmed that the amount of money inventors typically receive for patents is low and thus less important as a decision criterion than one might expect.

[10] Missing data about total employees affect 31% of the observations, also creating missing values in the *R&D Intensity* measure. To avoid underrepresentation of small and medium-sized firms, we employed a procedure proposed by Hall and Ziedonis (2001) and set the missing values to 0, then added a new dummy variable that takes a value of 1 when the value for the prior variable is missing (*R&D Intensity Missing Dummy*).

when they confront compensation plans that reward many low-value inventions. This result is robust across all specifications and robustness checks (as we detail subsequently) and supports Hypothesis 1.[11] In terms of effect size, the *False Positives* × *Corporate Scientists* interaction produces an elasticity of 29.2% for *R&D Working Hours*, equivalent to an average reduction of about four hours of R&D working time per week. The elasticity for *Interactions with R&D Colleagues* is 10.1%.[12]

To facilitate interpretation of the results, Figure 1 displays the marginal effects of the two regression models (Models 4 and 8 from Tables 5 and 6, respectively) for *Corporate Scientists* and other inventors. For example, an increase in *False Positives* from 0.04 (mean minus one standard deviation) to 0.44 (mean plus one standard deviation) results in a decrease of the *R&D Working Hours* of a corporate scientist from 17.26 to 13.91 (on average); likewise, *Interactions with R&D Colleagues* drop from 0.35 to 0.28. For other types of inventors, the same variation in *False Positives* produces negligible effects (increase in *R&D Working Hours* from 13.2 to 13.7, increase in *Interactions with R&D Colleagues* from 0.33 to 0.34).

The interaction between *False Negatives* and *Corporate Scientists* is not statistically significant. If we compare the interaction effects of *False Positives* × *Corporate Scientists* and *False Negatives* × *Corporate Scientists* (from Models 4 and 8, Tables 5 and 6), the Wald test of the differences between the coefficients is 3.57 for *R&D Working Hours* and 4.86 for *Interactions with R&D Colleagues*. These tests are significant at the 5% and 1% levels, respectively, in support of Hypotheses 2a and 2b.

To address Hypothesis 3, we split the sample according to the median value of *Firm Patents* (Table 7). The *False Positives* × *Corporate Scientists* interaction term is significantly weaker when *Firm Patents* is below the sample median, for both *R&D Working Hours* and *Interactions with R&D Colleagues*. The *F*-tests of the differences between the coefficients in the two groups equals 3.53 for *R&D Working Hours* and 4.91 for *Interactions with R&D Colleagues*. These tests are significant at the 5% and 1% levels, respectively. In other words, if firms have many patents, the negative interactions between *False Positives* and *Corporate Scientists* are stronger, in support of Hypotheses 3a and 3b.[13]

Estimates for firms with many patents (above the median) may have smaller standard errors (due to the larger number of patents and thus more robust information) than those for firms with fewer patents. However, with regard to the results in Table 7, for *R&D Working Hours* as the dependent variable, the standard errors of the interaction term (*False Positives* × *Corporate Scientists*) are 72% greater for firms with many patents than for firms with fewer patents. For the *Interactions with R&D Colleagues* variable, the standard errors decrease by 49% for firms with many patents, but the increase in the effect size is much stronger from a relative standpoint and amounts to 166%. Therefore, we are confident that differences in the numbers of patents are unlikely to drive these findings through smaller standard errors. An alternative interpretation suggests that firms with many patents enable scientists to form stronger social identity-related processes. Although we cannot rule out this interpretation, it also does not contradict our theoretical approach.[14]

Because our study involves different levels of analysis (i.e., patent–inventor and firm), we employed two alternative approaches to confirm that our results are not driven by the use of an OLS model or the aggregation procedure (from patent to firm level). First, we employed a multilevel, mixed-effects linear regression model that accounts for the patent–inventor and firm levels of observation. Second, because the aggregated variables at the firm level might vary in their reliabilities, depending on the numbers of observed patent–inventor pairs per firm, we performed our regressions on three

[11] We estimated our model with cross-sectional data, because the firm-level variables exhibit little variation over the three-year period that we observe. However, this approach may lead to simultaneity issues. As a robustness check, we estimated the regressions with a one-year lag in the core covariates *False Positives*$_{(t-1)}$ and *False Negatives*$_{(t-1)}$, relative to inventors' behaviors measured at *t*. Although we lose about one-third of the observations, the estimated results are similar to those in Tables 5 and 6.

[12] We calculated these elasticities using the STATA command eyex, as $d(\log y)/d(\log x)$, such that they indicate the marginal variation of *y* relative to the marginal variation of *x*.

[13] In an alternative test of Hypothesis 3, we estimated a three-way interaction effect of *False Positives* × *Corporate Scientists* × *Firm Patents*. The effect is negative, as expected, and statistically significant at the 10% level for *R&D Working Hours* and the 1% level for *Interactions with R&D colleagues*. All other results remain virtually unchanged.

[14] We thank an anonymous reviewer for providing this insight.

TABLE 4
Descriptive Statistics and Pairwise Correlations

		Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8
1	*R&D Working Hours*	13.91	14.63	0	95	1							
2	*Interactions with R&D colleagues*	0.34	0.21	−0.56	0.67	0.01	1						
3	*False Positives*	0.19	0.15	0	1	−0.14	0.06	1					
4	*False Negatives*	0.07	0.09	0	1	0.07	−0.03	−0.23	1				
5	*Corporate Scientists*	0.17	0.38	0	1	0.12	−0.02	−0.06	0.02	1			
6	*Autonomy*	3.48	1.2	1	5	0.11	−0.04	−0.05	−0.01	0.08	1		
7	*Reward Size Standard Deviation*	3.63	5.06	0	46.04	−0.08	0.05	0.2	−0.16	0.03	−0.02	1	
8	*Working Hours*	43.54	14.1	0	100	0.33	−0.02	−0.04	0.1	0.02	0.03	−0.07	1
9	*Inventor's Past Publications*	6.94	15.39	0	240	0.11	0.05	−0.06	−0.04	0.11	0.09	0.02	0.07
10	*Work Environment*	4.03	1.09	1	5	0.02	0.07	0.04	−0.06	0.02	0.12	0.08	−0.01
11	*Income*	3.6	1.2	1	5	−0.08	0.01	0.03	0.03	0.01	−0.01	0.02	0.03
12	*Experience*	2.49	0.8	0	4.54	−0.01	−0.09	−0.04	−0.02	0.03	0.08	0.03	0.04
13	*Gender Dummy*	0.96	0.19	0	1	−0.02	−0.05	0.04	0.03	−0.03	−0.01	−0.02	0.01
14	*PhD Dummy*	0.28	0.45	0	1	0.12	0.06	−0.08	−0.02	0.08	0.11	0.03	0.06
15	*Bachelor's or Master's Dummy*	0.63	0.48	0	1	−0.09	−0.01	0.11	0.01	−0.08	−0.1	−0.02	0
16	*Large Firm Dummy*	0.91	0.28	0	1	−0.03	0.08	0.09	0.02	−0.03	−0.04	0	0.01
17	*Medium Firm Dummy*	0.05	0.21	0	1	0.02	−0.06	−0.07	−0.02	0.02	0.02	0.01	−0.02
18	*Inventor's Past Inventions*	39.58	64.12	1	1000	0.04	−0.01	−0.03	0.04	0.06	0.02	−0.02	0.12
19	*Teamwork Dummy*	0.82	0.39	0	1	0.07	0.07	−0.07	0.01	−0.01	0.02	−0.03	0.04
20	*R&D Intensity*	0.21	0.32	0	1	0.02	0.08	0.04	−0.06	0.06	0.05	0.11	0.02
21	*R&D Intensity Missing Dummy*	0.31	0.46	0	1	−0.06	0.07	0.09	−0.03	−0.06	−0.08	0.05	−0.01
22	*Firm Patents*	3.22	1.34	1.1	6.25	−0.13	0.16	0.22	−0.11	−0.04	−0.05	0.33	−0.01
23	*Project Size*	2.02	1.22	0	4.45	0.33	0.01	−0.18	0.09	0.06	0.08	−0.09	0.14
24	*Funding Dummy*	0.91	0.29	0	1	0.01	0.02	−0.01	0.02	0	0.02	0.01	0.01
25	*Patent Family Dummy*	0.4	0.49	0	1	0.15	−0.02	−0.09	0.04	0.04	0.04	−0.02	0.07

separate subsamples; namely, the top 30%, 50%, and 70% of firms in terms of their number of patents and inventors. With both these analyses (results available on request), we fully confirm the central results of our estimations.

Finally, the control variables behave mostly as expected. *Corporate Scientists* work more hours on R&D projects; the relationship with *Interactions with R&D Colleagues* is also positive, though statistically weaker. A stimulating *Work Environment* positively correlates with the number of hours worked on R&D projects and with interactions inside the R&D department. *Autonomy* has a positive correlation with *R&D Working Hours* and a negative relationship with *Interactions with R&D Colleagues*, suggesting that inventors with high levels of autonomy focus more on R&D and look outside their departments as a source of inspiration; however, autonomy might also imply greater managerial responsibilities, including cross-departmental tasks. *Working Hours* behaves similarly to *Autonomy*. Inventors' *Income* and *Experience* correlate negatively with *R&D Working Hours.* More experienced inventors dedicate less time to R&D activities than younger researchers do, and interact more with people in other departments. Inventors involved in *Teamwork* allocate less time to R&D, but focus more on interactions in their department. In firms with many *Firm Patents*, inventors work fewer R&D hours and have more interactions with colleagues in the R&D department. However, the counterintuitive sign of *Firm Patents* on *R&D Working Hours* should be cautiously interpreted together with the positive sign of *Patent Family.*

VALIDATIONS AND ROBUSTNESS CHECKS

Heterogeneity in Reward Size and Autonomy

To check the robustness of our results further, we performed our main regressions (Tables 5 and 6) for two subsamples of observations, above and below the

TABLE 4
(Continued)

9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1															
0.04	1														
−0.03	0.01	1													
0.18	0.03	0.15	1												
−0.03	−0.01	0.07	0.07	1											
0.45	0.1	0.03	0.15	−0.05	1										
−0.34	−0.08	0.02	−0.16	0.02	−0.8	1									
−0.02	0.04	0.06	0.01	0.05	0.01	0.03	1								
−0.02	−0.03	−0.02	0.01	−0.01	−0.02	−0.03	−0.72	1							
0.11	−0.06	0.02	0.21	0.06	0.03	−0.03	0.06	−0.04	1						
0.06	0.06	−0.03	−0.06	−0.05	0.08	−0.05	0.03	−0.02	0	1					
0.11	0.07	−0.02	0.05	−0.03	0.12	−0.08	−0.24	0.08	0.04	0.01	1				
−0.09	−0.02	0.03	−0.09	−0.03	−0.08	0.1	0.15	−0.12	−0.03	−0.02	−0.42	1			
0	0.07	0.09	−0.01	0.02	0.04	0.03	0.17	−0.13	0.07	0.01	0.13	0.22	1		
0.11	−0.01	−0.04	−0.01	−0.07	0.09	−0.04	0	−0.02	0	0.21	0.03	−0.04	−0.08	1	
0.05	0.02	0.04	0.02	0.03	0.08	−0.05	0.06	−0.03	0.01	0.03	−0.03	0.01	0.01	0.05	1
0.1	−0.04	−0.01	0.08	0.01	0.08	−0.05	0.02	−0.02	0.16	0.1	0.02	−0.07	0	0.21	0.03

Notes: 3,955 observations.

median value for the *Reward Size Standard Deviation* variable. The results (available on request) reveal that the interaction term *False Positives* × *Corporate Scientists* maintains its negative sign in both subsamples, though its statistical significance is stronger in the low dispersion sample where rewards for patents are more similar in size. This evidence supports our general model: corporate scientists interpret false positives more negatively when the rewards for patents are less differentiated in their monetary amounts. Regressions with firms' average reward size or the individual size of a monetary reward confirm our results and do not alter the coefficients of interest strongly. Moreover, the individual reward size turns out to be statistically insignificant for predicting inventor behaviors.

On the basis of our underlying theory, we also assumed that inventors had sufficient freedom to choose their working time and interaction partners. Empirically, we controlled for *Autonomy*. As a further check, we once again created two subsamples, according to levels of *Autonomy* above or below the median. The *False Positives* × *Corporate Scientists* effect is of similar magnitude in both subsamples for *R&D Working Hours*. However, the statistical significance is below standard levels for low *Autonomy* inventors. In the case of *Interactions with R&D Colleagues*, the effect is much stronger in both magnitude and statistical significance among the sample of inventors who enjoy higher autonomy. Finally, a survey question asked whether inventors could make individual decisions about team inventions, so we ran our main regressions on two subsamples of inventors for whom autonomy in teamwork is either above or below the median value. The coefficient for *False Positives* × *Corporate Scientists* is negative in both samples, but both the magnitude and statistical significance are lower when autonomy in teamwork

TABLE 5
OLS Regressions: R&D Working Hours

	R&D Working Hours			
	Model 1	**Model 2**	**Model 3**	**Model 4**
*False Positives * Corporate Scientists*			−9.073***	−9.550***
			(3.427)	(3.598)
*False Negatives * Corporate Scientists*				1.176
				(1.597)
False Positives		−0.546	1.079	3.577
		(1.539)	(1.583)	(2.742)
False Negatives		3.046	2.850	−2.941
		(2.354)	(2.346)	(5.533)
Corporate Scientists	2.648***	2.605***	4.299***	4.599***
	(0.563)	(0.563)	(0.843)	(1.017)
Autonomy	0.478***	0.478***	0.485***	0.483***
	(0.171)	(0.171)	(0.170)	(0.170)
Reward Size Standard Deviation	0.020	0.027	0.027	0.027
	(0.045)	(0.046)	(0.045)	(0.045)
Working Hours	0.316***	0.316***	0.316***	0.315***
	(0.017)	(0.017)	(0.017)	(0.017)
Inventor's Past Publications	0.008	0.008	0.007	0.007
	(0.017)	(0.017)	(0.017)	(0.017)
Work Environment	0.506***	0.512***	0.523***	0.523***
	(0.186)	(0.186)	(0.186)	(0.186)
Income	−0.517***	−0.517***	−0.526***	−0.528***
	(0.164)	(0.164)	(0.163)	(0.163)
Experience	−1.158***	−1.151***	−1.132***	−1.138***
	(0.274)	(0.273)	(0.274)	(0.274)
Gender Dummy	2.292**	2.275**	2.250**	2.252**
	(1.099)	(1.100)	(1.092)	(1.092)
PhD Dummy	−0.399	−0.417	−0.400	−0.393
	(0.869)	(0.869)	(0.870)	(0.870)
Bachelor's or Master's Dummy	−1.299*	−1.289*	−1.280*	−1.275*
	(0.709)	(0.710)	(0.712)	(0.712)
Large Firm Dummy	−0.516	−0.483	−0.488	−0.507
	(0.947)	(0.945)	(0.938)	(0.937)
Medium Firm Dummy	0.284	0.315	0.320	0.328
	(1.237)	(1.237)	(1.238)	(1.237)
Inventor's Past Inventions	0.001	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Teamwork Dummy	−1.089**	−1.083**	−1.055**	−1.055**
	(0.517)	(0.516)	(0.518)	(0.518)
R&D Intensity	−0.031	−0.003	−0.019	−0.026
	(0.733)	(0.734)	(0.730)	(0.730)
R&D Intensity Missing Dummy	−0.412	−0.387	−0.395	−0.396
	(0.547)	(0.547)	(0.549)	(0.549)
Firm Patents	−0.659***	−0.637***	−0.618***	−0.620***
	(0.180)	(0.179)	(0.180)	(0.180)
Project Size	2.327***	2.308***	2.319***	2.317***
	(0.199)	(0.200)	(0.199)	(0.199)
Funding Dummy	−0.255	−0.255	−0.235	−0.235
	(0.711)	(0.710)	(0.714)	(0.715)
Patent Family Dummy	1.180***	1.167***	1.151***	1.152***
	(0.442)	(0.442)	(0.442)	(0.442)
Constant	−12.063***	−12.277***	−11.221***	−11.225***
	(4.387)	(4.397)	(2.595)	(2.594)
Observations	3,955	3,955	3,955	3,955
R-squared	0.306	0.306	0.307	0.307

Notes: Regressions include dummies for 30 technological classes, priority years, and country of the inventor. Robust standard errors clustered by firms in parentheses.

* $p < .10$
** $p < .05$
*** $p < .01$

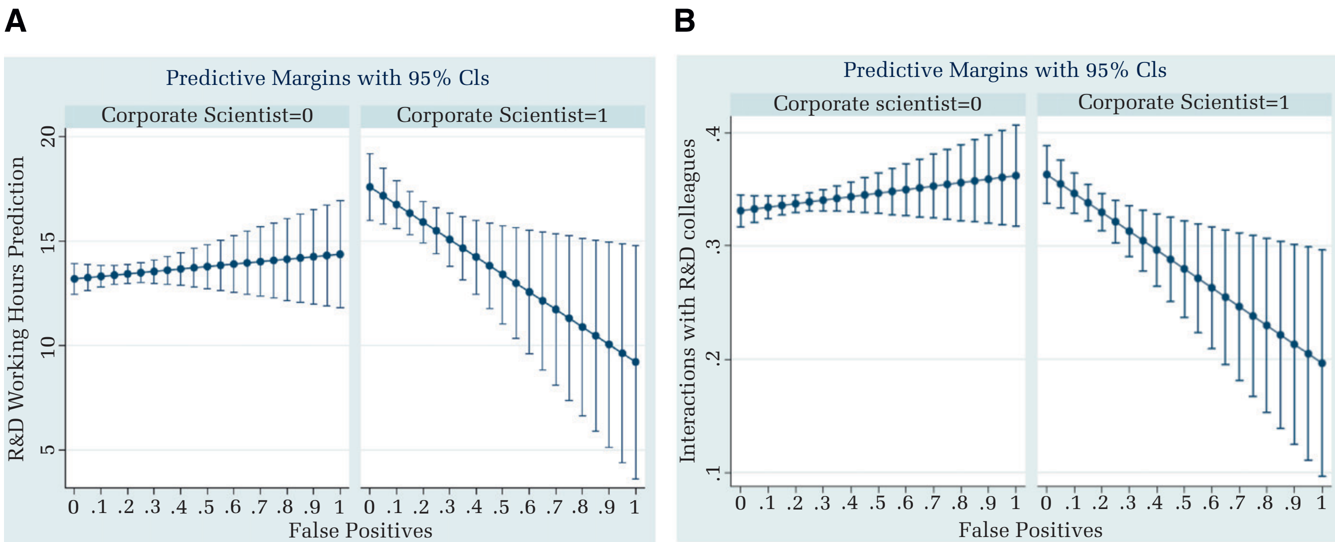
TABLE 6
OLS Regressions: Interactions with R&D Colleagues

	Interactions with R&D colleagues			
	Model 5	**Model 6**	**Model 7**	**Model 8**
*False Positives * Corporate Scientists*			−0.198***	−0.198***
			(0.063)	(0.065)
*False Negatives * Corporate Scientists*				0.031
				(0.028)
False Positives		−0.004	0.031	−0.017
		(0.027)	(0.028)	(0.045)
False Negatives		−0.013	−0.017	0.000
		(0.038)	(0.038)	(0.073)
Corporate Scientists	−0.005	−0.005	0.032**	0.032**
	(0.009)	(0.009)	(0.014)	(0.016)
Autonomy	−0.007**	−0.007**	−0.006**	−0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Reward Size Standard Deviation	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Working Hours	−0.001**	−0.001**	−0.001**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Inventor's Past Publications	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Work Environment	0.010***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.003	0.003	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Experience	−0.018***	−0.018***	−0.017***	−0.017***
	(0.005)	(0.005)	(0.005)	(0.005)
Gender Dummy	−0.037**	−0.037**	−0.037**	−0.037**
	(0.018)	(0.018)	(0.017)	(0.017)
PhD Dummy	0.023*	0.024*	0.024*	0.024*
	(0.013)	(0.013)	(0.013)	(0.013)
Bachelor's or Master's Dummy	0.007	0.007	0.008	0.008
	(0.012)	(0.012)	(0.012)	(0.012)
Large Firm Dummy	0.041**	0.041**	0.041**	0.041**
	(0.018)	(0.018)	(0.018)	(0.018)
Medium Firm Dummy	0.011	0.011	0.011	0.011
	(0.022)	(0.022)	(0.022)	(0.022)
Inventor's Past Inventions	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Teamwork Dummy	0.037***	0.037***	0.037***	0.037***
	(0.010)	(0.010)	(0.010)	(0.010)
R&D Intensity	0.050***	0.050***	0.050***	0.050***
	(0.013)	(0.013)	(0.013)	(0.013)
R&D Intensity Missing Dummy	0.021***	0.021***	0.021***	0.021***
	(0.008)	(0.008)	(0.008)	(0.008)
Firm Patents	0.012***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
Project Size	−0.005	−0.005	−0.005	−0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Funding Dummy	0.023*	0.023*	0.023*	0.023*
	(0.012)	(0.012)	(0.012)	(0.012)
Patent Family Dummy	−0.010	−0.010	−0.011	−0.011
	(0.007)	(0.007)	(0.006)	(0.006)
Constant	0.078	0.080	0.031	0.031
	(0.065)	(0.065)	(0.045)	(0.045)
Observations	3,955	3,955	3,955	3,955
R-squared	0.134	0.134	0.137	0.137

Notes: Regressions include dummies for 30 technological classes, priority years, and country of the inventor. Robust standard errors clustered by firms in parentheses.

* $p < .10$
** $p < .05$
*** $p < .01$

FIGURE 1
Marginal Effects from Regressions in Table 5 (Model 4) and Table 6 (Model 8)



Notes: Panel (a) R&D Working Hours and Panel (b) Interactions with R&D Colleagues.

is limited, suggesting once again that autonomy is an important moderator (results available on request).[15]

Recall Bias

Our key measures were collected in retrospect, so we checked whether the inventors' recollections were reliable. First, we estimated the predicted errors of regressions that use the inventors' self-reported monetary value as the dependent variable and, as covariates, standard proxies of patent value (i.e., forward citations, patent claims, and the number of patents belonging to the patent family). Observations with larger residuals likely indicate less reliable memory (i.e., relatively greater recall bias). In that case, we can employ the predicted errors to assess whether potential recall biases correlate with the variables of interest of our study.

We first aggregated the predicted errors to the firm level and add them to firm-level models of *False Positives* and *False Negatives* to analyze whether this potential recall bias affects our firm-level measures of false rewards. We then used the predicted errors in the main regressions at the inventor–patent level. The predicted errors do not correlate with the reported amount of *R&D Working Hours* or with firms' *False Positives* and *False Negatives*. However, we found a small and positive correlation with the average *Interactions with R&D Colleagues*, indicating that people might find it difficult to recollect the specific amount of time they spent in interactions with different groups of colleagues. As an additional check, we replicated our main regressions, excluding all cases with high predicted errors—that is, for the top 10% or 25% of the error distribution. The estimated results (available on request) confirm our main findings.

We also checked whether our respondents might suffer from a "rumination" bias (Delgado-Rodriguez & Llorca, 2004), such that they might alter their perceptions of past experiences *ex post* due to their effort to recall information in a search for causes. To this end, we conducted a follow-up survey that experimentally invoked a rumination process. A six-question survey, targeted at 610 randomly selected inventors from the 3,955 observations of our sample,

[15] To address whether corporate scientist effects are due to other characteristics that differentiate them from other types of inventors, such as the level of education, we also defined corporate scientists as those with a doctoral degree. In another robustness check, we differentiated them by field of study, distinguishing pure science (e.g., mathematics, physics) from applied science (e.g., engineering, computer science). These alternative definitions do not produce statistically significant results in our regressions, which lends support to our theory and definition of corporate inventors based on their working motivations instead of more manifest differences (e.g., holding a doctoral or pure science degree).

TABLE 7
OLS Regressions with Subsamples Above and Below the Median of Firm Patents

	R&D Working Hours		*Interactions with R&D Colleagues*	
	Below Median	***Above Median***	***Below Median***	***Above Median***
*False Positives * Corporate Scientists*	−8.281*	−20.763***	−0.086	−0.229***
	(4.442)	(7.652)	(0.151)	(0.077)
*False Negatives * Corporate Scientists*	2.426	−5.901	0.066	0.028
	(1.775)	(3.710)	(0.095)	(0.030)
False Positives	4.616	−7.518	0.012	−0.027
	(2.949)	(7.909)	(0.176)	(0.046)
False Negatives	−1.802	−11.306	0.077	0.024
	(5.839)	(22.728)	(0.257)	(0.077)
Corporate Scientists	3.504***	8.263***	0.006	0.031*
	(1.215)	(2.731)	(0.042)	(0.018)
Autonomy	0.624**	0.425**	−0.006	−0.007
	(0.271)	(0.213)	(0.004)	(0.004)
Reward Size Standard Deviation	−0.078	0.097	0.001	−0.000
	(0.051)	(0.073)	(0.001)	(0.002)
Working Hours	0.363***	0.281***	−0.000	−0.001
	(0.025)	(0.021)	(0.000)	(0.000)
Inventor's Past Publications	−0.029	0.046*	0.000	0.000
	(0.021)	(0.025)	(0.000)	(0.000)
Work Environment	0.542*	0.512**	0.010**	0.008*
	(0.282)	(0.246)	(0.005)	(0.004)
Income	−0.409	−0.540***	−0.003	0.006
	(0.261)	(0.197)	(0.004)	(0.004)
Experience	−1.003**	−1.246***	−0.019***	−0.017**
	(0.415)	(0.362)	(0.007)	(0.007)
Gender Dummy	2.360	2.162	−0.033	−0.037
	(1.713)	(1.368)	(0.023)	(0.026)
PhD Dummy	−1.430	0.991	0.017	0.028
	(1.178)	(1.300)	(0.021)	(0.018)
Bachelor's or Master's Dummy	−2.447***	0.603	−0.005	0.020
	(0.946)	(1.089)	(0.022)	(0.015)
Large Firm Dummy	0.575	−3.202**	0.019	0.040*
	(1.299)	(1.457)	(0.035)	(0.021)
Medium Firm Dummy	1.207	−1.464	0.014	0.008
	(1.593)	(2.132)	(0.041)	(0.027)
Inventor's Past Inventions	0.001	0.002	−0.000	−0.000
	(0.007)	(0.005)	(0.000)	(0.000)
Teamwork Dummy	−0.311	−1.741**	0.047***	0.026**
	(0.759)	(0.728)	(0.015)	(0.012)
R&D Intensity	2.542*	−1.326	0.042**	0.055**
	(1.377)	(0.918)	(0.017)	(0.022)
R&D Intensity Missing Dummy	−0.488	−0.384	0.019*	0.014
	(0.794)	(0.782)	(0.011)	(0.012)
Firm Patents	2.422***	2.248***	−0.003	−0.007*
	(0.292)	(0.284)	(0.005)	(0.004)
Project Size	0.183	−0.728	0.029*	0.005
	(1.108)	(0.946)	(0.015)	(0.018)
Funding Dummy	0.942	1.429**	−0.010	−0.011
	(0.675)	(0.599)	(0.009)	(0.010)
Patent Family Dummy	0.199	−0.657**	−0.007	0.022***
	(0.479)	(0.330)	(0.007)	(0.008)
Constant	−5.443	−6.541	0.153*	0.206***
	(3.459)	(4.169)	(0.078)	(0.062)
Observations	1,931	2,024	1,931	2,024
R-squared	0.326	0.307	0.131	0.144

Notes: All regressions include controls for the 30 technological classes of the patent, priority years, and country of the inventor. Robust standard errors clustered by firms in parentheses.

* $p < .10$
** $p < .05$
*** $p < .01$

asked them to reconsider the same patent on which our main empirical analysis is based (which we reattached to the new questionnaire). In this survey, we asked the inventors to confirm or modify some information they had provided in the original survey (i.e., whether they received a bonus for the patent, the number of total working hours, and the share of working hours dedicated to R&D activities). We also provided the inventors with information about the share of rewarded patents in their companies at the time of the invention (*Rewarded Patents* in Table 2). However, we randomly manipulated this information: Some inventors received the "true" information estimated from our data, whereas others saw "false" information (i.e., lower or higher than the sample median, whereas the "true" value was higher or lower, respectively).[16] If a rumination bias exists, this change to the initial conditions should affect the inventors' memories, such that those primed with "false" information may be more likely to "correct" their answers compared to a control group that receives "true" information. We obtained 84 valid responses (13.7% response rate). As Table 8 shows, the quasi-experiment produced no statistically significant differences between the treated and the control group, which we interpret as support for the data quality.

Individual-Level Incentive Effects or Violated Norms and Beliefs?

We have argued that corporate scientists identify with their "guild" (Mudambi & Swift, 2009) or "invisible college" (Gustin, 1973) and react negatively to false positives because they violate the shared norms and beliefs of the scientific community. An alternative reading of our results could be that false rewards have negative incentive effects, such that inventors are dissatisfied with the rewards that they *personally* receive for their work. To gauge whether this explanation applies to our context, we performed three regressions that, in addition to the covariates in Tables 5 and 6, include the following variables: (1) a dummy variable that equals 1 if the inventor received a reward for the patent (irrespective of the patent's quality), and 0 otherwise; (2) four dummy variables that each equal 1 if the inventor had or had not received a reward for a high-quality patent or for a low-quality patent, and 0 otherwise; and (3) the interactions of these reward dummies with *Corporate Scientists*. In all three regressions, the main results (available on request) remain unchanged.

[16] At the end of the questionnaire, the respondents were debriefed and received information about the survey's intention and the manipulation.

Stability of Motivations to Invent

Another critical question is how stable the inventors' motivations to invent are. Our *Corporate Scientist* dummy is based on a measure of these motivations, so if inventors reveal changing preferences over time, they might form alternative social categorization processes, which our theory assumes to be largely exogenous, at least in the short to medium run. Existing evidence supports our assumption. Based on data from U.S. scientists and engineers with doctoral degrees, Sauermann and Cohen (2010) found no strong signs of changes in job motivations over time. Although we did not observe the inventors in our survey repeatedly, we can use the repeated inventor observations obtained from an earlier, structurally very similar survey (PatVal-EU survey [Giuri et al., 2007]), conducted for the years 2003–2005. This earlier survey used data from approximately 9,550 inventors, similar sampling criteria, and similar methodologies. For a subsample of 573 inventors, this earlier survey contains interviews about two or more patents that each inventor had earned at different points in time. Similar to Sauermann and Cohen (2010), we explored whether these inventors' motivations remained stable over time and projects. The *t*-tests reveal insignificant mean differences in the importance of intellectual challenge (0.023, SD = 0.360) and scientific reputation (–0.003, SD = 0.342) across patents invented at different times by the same inventors. The correlations between motivations to invent and individual rewards are also low and negligible, such that the rewards–intellectual challenge correlation is 0.02, and the rewards–scientific reputation correlation is -0.02. Finally, *t*-tests of mean differences, performed separately for inventors who received a reward for a patent and those who did not, indicate no statistically significant changes in motivations, thus confirming that rewards and motivations do not affect each other strongly over time.

Additional Evidence from Interviews

We also briefly report on interviews that we conducted with four inventors from our survey (two Italians, one Spanish, one Swiss) whose characteristics reflected the inventor types in our study (i.e., one corporate scientist and three nonscientist inventors); a vice president (VP) of compensation and benefits of a large German innovative firm (listed within the 30 major German firms stock market index DAX) and

TABLE 8
Manipulation Checks in the Follow-Up Survey

	Original Values			
	Number of Responses	*Total Hours Worked*	*Share of R&D Hours*	*Reward Received*
Nonmanipulated	43	42.372	0.482	0.511
Manipulated	41	43.804	0.385	0.634
Difference		−1.432	0.097	−0.122
St. Err.		4.476	0.055	0.108
T-test		0.749	0.082	0.262
	Probability of Changed Answers After the Manipulation			
	Number of Responses	*Total Hours Worked*	*Share of R&D Hours*	*Reward Received*
Nonmanipulated	43	0.139	0.209	0.116
Manipulated	41	0.170	0.292	0.170
Difference		−0.031	−0.083	−0.054
St. Err.		0.079	0.095	0.077
T-test		0.697	0.383	0.481
Bartlett's test (Prob > chi^2)		0.597	0.474	0.307

a CEO or inventor of a high-tech start-up firm financed by venture capitalists. These interviews help us evaluate the practical validity of our theoretical framework. All interviews (except for the CEO or inventor interview, which took place via email) lasted about half an hour and were conducted personally by the authors; all four inventors' interviews were recorded, while the VP interview was not recorded, though careful notes were taken.

We asked the inventors to comment on three "statements" that reflect the backbone of our theory (Muhlemeyer, 1992; Randle, 1997): (1) a distinguishable community of corporate scientists exists within the general population of corporate inventors; (2) corporate scientists hold specific norms and beliefs, including a preference for highly selective (and not necessarily monetary) rewards; and (3) selective rewards reinforce the social identities of corporate scientists. The interviews with the VP and CEO focused more on the general setup and results of our study.

According to the VP, managers who grant rewards for patents are convinced of the patents' value, yet because no systematic evaluation of patent success takes place *ex post*, many firms reward too many patents, thus generating false positives and indicating that they do not know "how to do better." He also acknowledged that "scientists tick differently," such that his firm had abandoned individual-level PFP, with the belief that "engineers and inventors from the heart" should be creative without "all the incentive stuff," which instead appeared detrimental to their performance and well-being. The VP also agreed that corporate scientists are a visible social group within firms that embraces the values of scientists in academia.

The employee respondents similarly recognized the presence of a scientific "guild" that is driven by reputational needs ("to become known") and the desire to solve technical problems faster than others (especially before competitors). As the corporate scientist noted, "Since I was a kid, I was fascinated by solving problems, and when with my first job I joined the R&D lab of [Company] it was like being in heaven," marked by "meetings among us [corporate scientists] during the coffee break that lasted longer than one hour and centered on the discussion of technical problems, with no contact with other people." He further affirmed that he sought to become the "reference person," a sort of living encyclopedia whom people could consult. He confirmed that prizes were less about money than about a feeling of "being loved and appreciated by the company." In contrast, the nonscientists realized that they were not a part of the scientific community, whose existence they nevertheless acknowledged. These informants cautioned that "if your payroll and monetary benefits depend on reaching a certain number of patents, this kills creative people," and "a monetary reward for an invention has a different value if it is not exclusive and everybody gets it."

Finally, according to the CEO–inventor, patents, rather than rewards for those patents, provide the means to gain recognition from peers. A monetary bonus associated with a patent does not provide much of an incentive to inventors; the size of such prizes is typically small. He therefore proposed that a better strategy would be to "provide fewer rewards of a larger size and higher prestige only to the few inventions that contribute to a large extent to the firm's sales."

DISCUSSION

In the context of industrial research that produces patented inventions, firms potentially generate two types of false rewards: They may reward low-quality inventions (false positives) or overlook high-quality inventions (false negatives). We have posited and shown that industrial inventors driven by the desire to solve technical challenges and achieve peer community recognition (Gustin, 1973; Merton, 1973; Roach & Sauermann, 2010; Stern, 2004)—or corporate scientists, in our terminology—withdraw from R&D projects and from interactions with their peers in R&D when their firms generate many false positives. Our argument builds on social comparison processes (Tajfel & Turner, 1986), in the sense that false positives endanger these individuals' beliefs, as exhibited in priority rules and winner-take-all incentive structures (Mudambi & Swift, 2009; Stephan, 1996). With data on 3,955 patent–inventor observations from a worldwide survey of inventors, we found support for our arguments, and we also ruled out some alternative explanations for the observed correlations.

Theoretical Implications and Further Research

Different combinations of employee motivations and PFP practices may have distinct behavioral effects (e.g., Chng et al., 2012; Larkin et al., 2012; Wowak & Hambrick, 2010). We argue that these differential effects are particularly visible when groups of employees identify strongly with external communities or social groups whose belief systems, rules, and norms interfere with the firm's compensation practices. In our study setting, we find support for this effect among corporate scientists, relative to the more general population of inventors (Mudambi & Swift, 2009). The same logic and trade-offs might apply to other cases, in which companies deliberately hire employees with a strong sense of community, yet the community's beliefs and rules interfere with the firm's practices. For example, software houses often hire from open software communities, like IBM from the Apache Spark project (O'Mahony & Ferraro, 2007); Apple's first R&D lab was partially built around John Draper and the hacker community of Silicon Valley. Our findings also might extend beyond the R&D and high-tech context to for-profit firms that hire employees trained in nonprofit or volunteer-based organizations, in an effort to comply with social responsibility objectives (Battilana, Sengul, Pache, & Model, 2015). Further research could investigate the extent to which a strong sense of belonging to internal or external communities requires trade-offs.

Our study also helps specify the effectiveness of PFP in creative and innovative settings (Fang & Gerhart, 2015). Researchers offer various explanations for why PFP may create spectacular results when it works, or spectacularly bad results if it fails, including crowding out intrinsic motivation (Deci, Koestner, & Ryan, 1999; Frey & Jegen, 2001), substitution of norms with a prize (Gneezy & Rustichini, 2000), or the failure of motivation to lead to actual performance (Ariely, Gneezy, Loewenstein, & Mazar, 2009). In an innovative or creative setting, researchers typically assert either that PFP undermines intrinsic motivations and is harmful (Deci et al., 1999) or that its negative effects for creativity can be avoided by leveraging the feedback, rather than the controlling, character of rewards (Cameron & Pierce, 1994; Fang & Gerhart, 2015). Behavioral feedback (or information) provided through rewards has more than one dimension, though, such that it produces individual perceptions and interpretations of the firm's expectations and strategies, which further complicates the relationship.

Another theoretical implication relates to the concepts of *False Positives* and *False Negatives*. PFP requires performance appraisals, which can be behavior or output based (Rynes et al., 2005). These appraisals affect the future performance of employees through two routes: developmental feedback or rewards and punishments. Psychological research has focused almost exclusively on the feedback path. As Rynes et al. (2005: 573) lamented, the "relative neglect of the administrative function of PE [performance evaluation] by research psychologists has become so notable in recent years that the most recent Annual Review of Psychology chapter on PE . . . did not even mention research linking PE to pay or other rewards." In this sense, our work contributes to research that has linked performance appraisals and rewards. Continued research could focus more clearly on what makes different forms of performance assessment reliable and valid, as well as how unreliable or systematically distorted appraisals might affect employees' future behaviors through an effect on compensation systems. False rewards are only one of the potential consequences of imperfect performance assessments, but they constitute an important idea that deserves more research attention.

A fourth theoretical implication relates to the sorting function of compensation systems (Gerhart et al., 2009; Lazear, 2000; Shaw, 2015). We make an implicit assumption of limited turnover, but mismatches between firms' compensation systems and inventor motivations may result in employees' internal withdrawal behaviors or turnover. Generally, people are attracted to, selected into, and remain with organizations that fit their values and motivations (Bangerter et al., 2012; Schneider, 1987). Although quitting is a common phenomenon in many labor markets (e.g., Hom, Roberson, & Ellis, 2008; Lee, Gerhart, Weller, & Trevor, 2008), our sample revealed an average organizational tenure of 14.4 years for corporate scientists and 13.8 years for other inventors. Furthermore, only 108 of 694 corporate scientists and 469 of 3,301 other inventors had changed their jobs in the five years before the survey, indicating an (average) annual quitting probability for corporate scientists of 3.3%, compared with 3.0% for other inventors.

The inventors in our sample had substantial autonomy (62% of corporate scientists reported a score of 4 or 5 on the five-point *Autonomy* scale, compared with 52% of nonscientists), so that autonomy might counterbalance some other negative work characteristics, such as a misfit with the pay system, and thus reduce the risk of quitting (Coff, 1997). This reasoning arose in our interviews, but other explanations also are plausible. The labor market for inventors is typically sticky, because it is unclear where and when R&D budgets will materialize or how sustainable they are. Stephan (1996: 1215) noted that "reliable forecasts of scientific labor markets do not exist" because the "ups and downs of federal funding make forecasts of scientific labor markets particularly unreliable." Data problems, a limited understanding of the pertinent institutions (e.g., corporations with varying R&D expenditures), and poor estimates of educational parameters (e.g., undergraduate enrollment and degrees) also might cloud the R&D labor market (Stephan, 1996). Furthermore, inventors tend to accumulate disproportionate amounts of tacit, firm-specific knowledge, which might limit their mobility (Campbell, Coff, & Kryscynski, 2012), as do noncompete clauses in employment contracts (Conti, 2014; Marx, Strumsky, & Fleming, 2009). Overall, the mismatches between compensation systems and inventor motivations are more persistent in our data than we might have predicted. When these mismatches persist, they may lead employees to engage in either psychological adjustment or firm-internal withdrawal behaviors, as we have argued and shown.

Managerial Implications

Our results suggest that internal withdrawal behaviors are strategically important. From a predictive and proactive perspective, managers should recognize that increasing the number of rewards for patents likely will result in more false positives but in a relatively smaller decrease in false negatives. They should also be aware that a change to the compensation system could have both positive and negative effects, but corporate scientists are likely to react negatively to increased reward breadth. Work motivations are difficult to observe, and it would be difficult to identify corporate scientists in an *ex ante* effort to control their behaviors. However, managers can carefully monitor signs of dissatisfaction and changes in behavior, especially after any change to the firm's compensation system.

Accordingly, companies may realize that universal PFP mechanisms are unlikely. Employees are members of various external and internal social groups that shape their social identities. The firm's practices might be at odds with some of these groups' values and beliefs, and mismatches can be critical. To create more positive incentives for employees, firms should fine-tune PFP processes. For example, false rewards are more likely for patents when managers with scarce knowledge about R&D processes design the compensation system (Berg, 2016). They also tend to be more common when PFP processes are poorly designed or politically biased (Harhoff & Hoisl, 2007). Findings from an economics of innovation perspective (Gambardella, Harhoff, & Verspagen, 2008) have shown that observable patent characteristics predict the future value of inventions. These characteristics in turn might be used to improve compensation systems and reduce false rewards. As complex managerial practices that serve different purposes and feature manifold uncertainties, compensation systems demand further research that can disentangle the contingencies of the partly contradicting forces and their interactions with employee motivations to predict their ultimate effects on employee behaviors and firm performance.

Limitations

Our data might suffer from aggregation and measurement issues due to the complex survey structure. Another concern with survey data is that the relationships among the variables could be spuriously inflated due to common method bias that might arise from implicit theories that uniformly drive the respondents' answers to different survey questions, or from the priming effects of colocated questions. We cannot completely rule out these concerns, but the survey design likely limited these issues. Similar to other R&D surveys (e.g., Cassiman & Veugelers, 2006), our questionnaire was not designed solely to inform the current research, so priming factors or implicit theories about PFP policies on inventors' reactions are unlikely. The key study constructs (time devoted to R&D, frequency of interactions with close colleagues, motivations) were measured with different scales, and their correlations were low, such that they appeared to capture distinct constructs. The key survey questions appeared on different pages and sections of the survey instrument, further limiting such concerns (Podsakoff, MacKenzie, & Lee, 2003).

We report regression estimates consistent with our theory and rule out several alternative explanations. Still, given the cross-sectional nature of our data, we cannot prove causality or completely exclude the possibility that other unobserved factors contributed to our results. The mechanism that we present lends itself to laboratory experiments and scenario studies (Aguinis & Bradley, 2014; Aiman-Smith, Scullen, & Barr, 2002), so we look forward to research that tests our hypotheses and attempts to replicate our results.

CONCLUSION

With data from a worldwide inventor survey, we analyzed the effects of two types of false rewards—false positives and false negatives—on inventor behaviors. We hypothesized and empirically found sound correlations to indicate that corporate scientists tend to withdraw from R&D activities and their closest peers in the R&D department when their firms grant many false-positive rewards. Our results might generalize to related settings in which organizational members derive important parts of their social identities from social groups whose belief systems or rules are in conflict with salient organizational practices.

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Marco S. Giarratana (marco.giarratana@ie.edu) is professor of corporate and competitive strategy at IE Business School, IE University, Madrid, Spain. He received his PhD in Economics & Management at the Sant'Anna School of Advanced Studies, Pisa, Italy. His research focuses on diversification, product strategies, innovation, and strategies for social business hybrids.

Myriam Mariani (myriam.mariani@unibocconi.it) is associate professor at Bocconi University, Milan and director of the Master of Science Program Economics and Management of Innovation and Technology. She earned a PhD in Business from Marche Polytechnic University, Italy. Her research interests are in the drivers of income and productivity differences among knowledge workers, including job motivations and knowledge spillovers among individuals and firms.

Ingo Weller (weller@bwl.lmu.de) is professor of management at the Munich School of Management, LMU Munich, Germany. He received his PhD from the University of Flensburg, Germany. His primary interests include strategic human capital research, matching processes, and the science and practice of people analytics.

APPENDIX A
Simulation of False Positives and False Negatives under Different Reward Schemes

	Random selection				Perfect selection				Informed selection				Twofold selection			
% of rewarded patents (reward breadth)	10	20	40	80	10	20	40	80	10	20	40	80	10	20	40	80
Number of high-value patents, rewarded	1.5	3	6	12	10	15	15	15	2.61	5.22	10.43	15	5.53	10.56	15	15
False negatives (FN): Number of high-value patents, not rewarded	13.5	12	9	3	5	0	0	0	12.39	9.78	4.57	0	9.47	4.44	0	0
Share of FN = FN/all patents	0.135	0.12	0.09	0.03	0.05	0	0	0	0.124	0.098	0.046	0	0.095	0.044	0	0
Change in share of FN per 10 percentage point increase of reward breadth		0.015	0.015	0.015		0.05	0	0		0.026	0.026	0.011		0.050	0.022	0
Low-value patents, unrewarded	76.5	68	51	17	85	80	60	20	77.61	70.22	55.43	20	80.53	75.56	60	20
False positives (FP): Number of low-value patents, rewarded	8.5	17	34	68	0	5	25	65	7.39	14.78	29.57	65	4.47	9.44	25	65
Share of FP = FP/all patents	0.085	0.17	0.34	0.68	0	0.05	0.25	0.65	0.074	0.148	0.296	0.65	0.045	0.094	0.25	0.65
Change in share of FP per 10 percentage point increase of reward breadth		0.085	0.085	0.085		0.05	0.1	0.1		0.074	0.074	0.089		0.050	0.078	0.1

Notes: Our simulation assumes 100 patents, of which 15 have a high value and 85 have a low value. Random selection uses a random draw from a uniform distribution to assign a reward to a patent. Perfect selection implies perfect knowledge, and high-value patents are rewarded first. For informed selection, high-quality patents have two times the probability of being rewarded compared to low-quality patents. Twofold selection implies that 50% of rewards are assigned to high-quality patents (via perfect selection), and 50% are assigned to all remaining patents. It is worth noting that twofold selection creates an asymmetric process, in which further increases in reward breadth produce relatively larger increases in false positives than decreases in false negatives. Twofold selection fits our empirically observed data patterns best.

APPENDIX B

SURVEY METHOD AND SAMPLE

The focal InnoS&T survey was conducted between 2009 and 2011 in 20 European countries, Israel, the United States, and Japan. From the EPASYS (an EPO database with all procedural data regarding European patent documents) database (04/2008), we selected all patent applications to the European Patent Office with priority dates between 2003 and 2005 with inventors living in any of the 23 countries surveyed, which provided us with 301,503 patent applications.

We had a goal of 21,000 valid answers. To achieve this, we sent the questionnaire to a random sample of 124,134 inventors: 50% in Europe and Israel, 13% in Japan, and 37% in the United States. We received 22,557 responses (20% corrected response rate).

For each patent document with more than one inventor, we selected a random inventor and sent an invitation letter asking him or her to fill out an online questionnaire that was accessible with a personal ID and password. Support letters from the European Commission and European Patent Office supplemented the invitation. We sent one reminder letter and one reminder postcard in Europe and Israel; we sent two reminder postcards in the United States and Japan.

The questionnaire was made available in 11 languages. It also consisted of seven sections concerning the following topics: (1) inventors' educational backgrounds, (2) employment and mobility, (3) invention process, (4) inventors' motivations and rewards, (5) use and value of the patent, (6) European Patent System, and (7) personal information.

We tested the questionnaire with three pretests. The first was conducted with groups of 25 randomly selected inventors per country (then not included in the final survey), and it aimed to check the survey procedure. A second pretest compared response rates of a paper-and-pencil survey against an online version. The third pretest aimed to receive direct comments from the inventors about the survey. We contacted inventors by telephone and asked, for example, about their experience with the survey or their reasons for not responding to it.

APPENDIX C
Variable Definitions

Variable	Description
R&D Working Hours	Number of weekly working hours typically spent on inventing activities at the time of the invention
Interactions with R&D Colleagues	(Frequency of interactions with R&D colleagues – Frequency of interactions with colleagues in other departments)/(Frequency of interactions with R&D colleagues + Frequency of interactions with colleagues in other departments). Frequency scale: 1 (never) to 5 (daily)
False Positives	Rewarded patents whose value is below the average value of patents in the same technological class, divided by all the firm's patents
False Negatives	Nonrewarded patents whose value is above the average value of patents in the same technological class, divided by all the firm's patents
Corporate Scientists	Dummy variable that takes a value of 1 for inventors who score above the median on two items: "prestige and reputation" and "intellectual challenge" (scales: 1 = not important to 5 = very important); the medians are 2 and 3, respectively
Autonomy	Inventor autonomy regarding the allocation of working time among different tasks or projects. Scale: 1 (no or low autonomy) to 5 (very high autonomy)
Reward Size Standard Deviation	Standard deviation of the reward size within firms, measured in thousands of euros
Working Hours	Number of average weekly hours worked at the time of the invention
Inventor's Past Publications	Number of articles published in scientific journals by the inventor
Work Environment	"The organization had a scientifically or technically stimulating environment;" Scale: 1 (completely disagree) to 5 (completely agree)
Income	Inventor's annual income. Scale: 1 (below 10k euros) to 6 (above 100k euros)
Experience	Log of number of years since the inventor has entered the "inventive" job
Gender Dummy	Inventor's gender dummy (1 for males)
PhD Dummy	Dummy variable: 1 if the inventor's highest degree is PhD
Bachelor's or Master's Dummy	Dummy variable: 1 if the inventor's highest degree is bachelor's/master's
Large Firm Dummy	Dummy variable: 1 for firms with more than 250 employees
Medium Firm Dummy	Dummy variable: 1 for firms with 50 to 250 employees
Inventor's Past Inventions	Number of previous inventions by the inventor
Teamwork Dummy	Dummy variable: 1 if the patent is a the result of teamwork
R&D Intensity	Ratio between a firm's R&D employees and total employees
R&D missing dummy	Dummy 1 if *R&D Intensity* is missing because of data on firm employees
Firm Patents	Log of number of firms' patents as computed from the survey
Project Size	Log of number of man-months employed to develop the invention
Funding Dummy	Dummy variable: 1 if the R&D project was directly financed by the firm's cash
Patent Family Dummy	Dummy variable: 1 if the patent is part of a family of patents. A patent family is defined as a group of patents filed by the same applicant(s), which crucially depend on each other in a technical way or in terms of their value.

Notes: Data taken from the InnoS&T survey.