

Competition and Productivity in Employee Promotion Contests

Bo Cowgill*

March 10, 2015

[Click here](#) for the most recent full version, or [email bo.cowgill@berkeley.edu](mailto:bo.cowgill@berkeley.edu).

Abstract

Why do firms use incentives that encourage anti-social behavior among employees? Rank-based promotion schemes are among the most widespread forms competition and incentives, despite encouraging influence-peddling, sabotage and anti-social behavior. I study a natural experiment using rich administrative data from a large, white collar firm. At the firm, competitors for promotions depend partly on dates-of-hire. I utilize the date-of-hire assignment as a source of exogenous variation in the intensity of intra-worker competition. I use the firm's multidimensional timestamped productivity logs as "time diaries" to study the amount, character and allocation of output across tasks. I find that competition has significant incentives for effort and efficiency – as well as lobbying- and sabotage- like behaviors – without affecting the quality and innovativeness of output. I also find that employees facing high competition are more likely to quit and join other companies, particularly higher-performing employees. Lastly, I show that competition induces workers to differentiate and specialize by concentrating effort into a smaller set of tasks. These results show that while workers respond to incentives from competition, they also seek to avoid it through sorting and differentiation strategies. The productivity gains from differentiation and specialization may partly explain the common use of these incentives by firms.

*The author thanks Ben Campbell, Jed DeVaro, Pieter De Vlieger, Frances Haugen, Pablo Hernandez, Mitch Hoffman, Joe Golden, Przemek Jeziorski, Preston McAfee, John Morgan, Hal Varian, Seth Stephens-Davidowitz, Steve Tadelis, Reed Walker, Noam Yuchtman, Owen Zidar and Eric Zitzewitz, as well as participants at the 2014 Consortium on Competitiveness and Cooperation Doctoral Conference, the 2014 Institutions & Innovation Conference and the Oliver Williamson Seminar at Berkeley/Haas.

1 Introduction

Competition between employees within a firm is among the most widespread forms of formal incentives. In America, intra-worker competition at the same firm is a feature of wage growth for 77% of the workforce.¹ Worker-vs-worker competition has been publicly championed as a management technique by high-profile business leaders including Jack Welch, Marissa Mayer and Steve Ballmer, and is a leading application for a growing formal literature on contest theory (Siegel, 2009).

Despite its prevalence, workplace competition has been widely criticized for encouraging sabotage (Dye, 1984) and influence-peddling (Milgrom and Roberts, 1988) in both academic and popular (Eichenwald, 2005; Swisher, 2013; Carlson, 2014) management circles. Are the potential productivity gains worth the risk of encouraging lobbying and anti-social behavior?

This paper studies the extent to which intra-worker competition affects workplace performance and behavior using a natural experiment. At the firm I study, competitors for promotions depend partly on dates-of-hire. I utilize this as a source of exogenous variation in the intensity of intra-worker competition in an instrumental variables setup.²

The outcomes I study come from the firm’s administrative data. The firm logs a wide variety of timestamped, labeled worker productivity data to facilitate collaboration and debugging. I use these activity logs as “time diaries” (Hamermesh et al., 2005) to analyze how competition affects the level and composition of worker effort. The data includes not only estimates of time spent, but also the quantity of output per-dimension using the firm’s internal task descriptions.³

I use this productivity and time use data to measure the effect of competition on worker effort – including not only the amount of effort, but also its efficiency, quality and allocation across multiple dimensions of productivity. For example, I study effects on innovation, productive on-the-job cooperation with colleagues, providing public goods for one’s peers and other economic characteristics of output (besides its amount). The multidimensional nature of output also permits analysis of specialization and the division of labor.

This paper has four main findings. First, I find that competition creates strong incentives for effort, output and efficiency, without decreases (or increases) in the quality or innovativeness of

¹This figure comes from a survey conducted for this paper of over 15,000 employed Americans, reweighted to match the census tracts. The survey and its results are described in Section 2.1 and reported in Table 1.

²The first stage has an F -statistic of ~ 31 .

³By contrast, traditional time use datasets usually measure only inputs (time) and not outputs. An additional advantage of this data is that it involves no self-reporting. Lastly, my data contains labels of activities designed by the firm, rather than by an external researcher. As such, the division of tasks I study in this paper aligns with the firm’s production function (or at least its self-perception thereof). They also assist with interpreting my results in light of the economic theory on incentives, contests and internal labor markets. Despite these advantages, these logs share some disadvantages with traditional time use data, described in Section 4.

output.⁴

Second, the competition does encourage several negative behaviors by employees. Workers report lower job satisfaction in competitive settings, and are less likely to be engaged in productive cooperation and organizational citizenship on several dimensions.

Third, I find that employees respond to the competition through sorting and retention decisions. Employees facing high competition sort into different competitive pools via quitting. Workers in high competitive situations are more likely to quit and join other companies. This is especially true for high-performing workers.

Fourth, I find that higher competition induces a different division of labor across workers. Competition affects not only the amount of output, but also its composition and division between workers. I find that competition induces differentiation and specialization by workers. As competition increases, workers increase the concentration of their effort into a subset of tasks.

This result has two interpretations. As early as [Smith \(1776\)](#), economists have viewed specialization and the division of labor within firms as a source of efficiency gains and a rationale for the existence of firms. In intra-worker competition, workers are likely to specialize in tasks where they hold comparative advantages against other contest opponents. The resulting productivity gains from specialization create additional efficiency benefits for the firm.

Specialization also makes comparisons between employees harder. A second interpretation of these results is that differentiation thus resembles a contest-theoretic version of differentiation ([Hotelling, 1929](#); [Tirole, 1988](#)) or “obfuscation” ([Ellison and Ellison, 2009](#)). By differentiating, workers can affect the noisiness of evaluation – a parameter set by the principal in most contest-theoretic models. Increases in evaluation noise decrease players’ equilibrium effort and increase player welfare.

Specialization thus benefits the worker and the firm, and dampens incentives for sabotage and influence-peddling. It thus represents a heretofore unrecognized benefit of rank-based competition, improving productivity and mitigating antisocial incentives. The effects of competition on the division of labor offer an additional and novel explanation for the widespread use of contests inside firms in multi-tasking environments, despite their negative side-effects on sabotage and politics.

This paper builds on several literatures. I use a methodological approach from the research on the economics of time use ([Aguiar et al., 2012](#)) to study a widespread phenomena at the intersection of labor economics and contract theory. Although I describe my data as “time diaries,” they differ in important ways from classical time use datasets and I discuss these differences in [Section 4](#).

⁴Although this result is consistent with most theory, some models of heterogeneity in workplace competition (i.e., [Gürtler and Gürtler, 2013](#)) predict the opposite results.

This paper is also the first to attempt to measure the prevalence of a tournament-like form of wage growth and incentives. Through a large survey, I collect new data to measure the pervasiveness of workplace tournaments: The results in Table 1 suggests they are a part of compensation for 77% of American workers. If anything, these figures may understate the prevalence of tournament-like rewards.⁵

The contract theory literature has embraced tournaments as a descriptive model of incentives within firms. Workplace contests are among the most common motivating applications of the theoretical tournament literature. An analysis of a natural experiment in stock option pricing by Cowgill and Zitzewitz (2009) suggests that promotion contests are a cheaper, more powerful form of incentives than stock options, even using the most generous estimates of the effects of options.

However, despite the central component of tournaments, the existing theoretical literature is mostly concerned with effort, sabotage and (to a lesser extent) “influence activities.” This paper shows the central role that sorting, differentiation, specialization and obfuscation may have in the context of workplace tournaments. One recent paper (Morgan et al., 2012) models self-selection into tournaments, but its theoretical predictions are ambiguous. There are few contest-theoretic papers with multidimensional effort at all.⁶

In addition, the empirical literature on contracting has narrowly focused on situations whereby we observe clear unidimensional measures of output (e.g., sports⁷ and manual labor⁸). In contrast, this paper focuses on the allocation of effort across a multidimensional set of tasks, some of which involve more uncertainty (e.g. innovative activities). These are arguably more common workplace environments. These jobs require workers to not only follow manager instructions, but also to form judgments, strategize, take risks, innovate and specialize. The multidimensional nature of output introduces contracting issues around multitasking (Holmstrom and Milgrom, 1991; Baker, 1992), specialization, innovation and complementarities that aren’t captured in farming or athletic settings.

White-collar work also exhibits contracting and measurement features that naturally lend themselves to tournaments. One of the heralded benefits of contests is “it is not necessary to determine how much better one worker is than another; all that is needed is rank order information” (Prendergast, 1999). Managers in sports and fruit-picking can easily measure differences in employee output. It is thus unclear why industries such as sports and farms need tournament incentives at

⁵Behavioral economists and psychologists have argued that even without formal contest incentives, workers care about rank-order performance as they directly affect self-image (Benabou and Tirole, 2003; Köszegi, 2006; Maslow, 1943; McClelland et al., 1953) and convey status (Besley and Ghatak, 2008; Moldovanu et al., 2007; Frank, 1985).

⁶Two rare exceptions include Garicano and Palacios-Huerta (2005) and a very a brief discussion in Acemoglu and Jensen (2010). A related literature on auctions has studied multidimensional bidding, for example, Che (1993), Yoganarasimhan (2013) and Krasnokutskaya et al. (2013).

⁷For example, Brown (2011); Garicano and Palacios-Huerta (2005); Balafoutas et al. (2012); Becker and Huselid (1992).

⁸For example, Bandiera et al. (2013), Drago and Garvey (1998), Knoeber and Thurman (1994), Knoeber (1989).

all, rather than alternative contracts.

By contrast, managers in white collar work cannot easily measure differences in the market value of software output, patentable ideas or consulting advice – but can make reasonable rank comparisons. As such, these settings embody the information and contracting details that give rise to tournament incentives.

This paper also incorporates ideas from the larger literature on how firms mitigate competition, price wars and other forms of costly competition. In different contexts, economists and strategy researchers have addressed maneuvers to avoid or “soften” competition through differentiation ([Hotelling, 1929](#); [Tirole, 1988](#)), tacit or explicit collusion ([Stigler, 1964](#)), capacity restrictions, erecting barriers to entry ([Caves and Porter, 1977](#)) and/or “obfuscation” ([Ellison and Ellison, 2009](#); [Ellison and Wolitzky, 2012](#)).

This paper shows the applicability of these ideas from industrial organization in a labor and organizational economics setting. Like other competitive settings, contests are characterized by zero-expected profits through rent-dissipation. In most laboratory studies, rents are actually over-dissipated in contests ([Sheremeta, 2014](#)).

Lastly, this paper contributes to the literature on peer effects (e.g. [Sacerdote, 2011](#)). Much of the peer effects literature measures the homogenizing influence of peers on each other. However, the contest literature predicts a different type of peer effects in competitive settings. This paper demonstrates competition creating specialization and differentiation between peers, rather than homogenization. I also show evidence of endogenous self-sorting ([Carrell et al., 2013](#)) motivated by these competition-related peer effects. Tournament-like incentives exist in many of the settings wherein economists care about peer-effects; not only in firms, but also in classrooms where grades are often awarded on relative performances “curves” that create contest-like incentives.

The remainder of this paper is organized as follows. Section 2 describes the setting and details of the firm’s promotion practices. Section 3 describes the natural experiment, and Section 4 describes the data. Section 5 describes the empirical specifications and identification. Section 6 covers reduced form results. We conclude with a discussion in Section ??.

2 Setting and Institutional Details

The data in this paper comes from a large white-collar technology and services company. Employees at this firm are mostly software engineers, product managers, sales, marketing, and support staff. At this firm, promotions are a major component of incentives and compensation. After every quarter of performance, employees were evaluated subjectively and assigned a score on a one to five scale. [Carlson \(2014\)](#) describes a similar, five-point employee evaluation process used at

Yahoo. To limit managerial favoritism, scores were decided by a committee using input from the manager and peers.

Career progress and promotions at the firm were managed using job levels. Within each type of job, employees occupied a level which generally spanned from one (most junior) to nine (most senior). A promotion constituted a vertical move upwards on this ladder and was associated with a permanent increase in base salary of roughly 20%. This increase in base salary was the primary benefit of being promoted. Although the firm set higher performance expectations for each level,⁹ duties often do not significantly change after promotions. The promotion system at this firm is thus mostly about providing incentives, and not selecting the best candidate for a different role.

Promotion decisions were made twice per year. To initiate a promotion, a worker must agree to be nominated. Workers can self-nominate, or be nominated by a manager. The manager's support is a valuable but not required condition for promotion. Like subjective performance evaluations, the promotion decision is made by a committee to avoid managerial bias and conflicts of interest. According to analysts at the firm, a small number of employees succeed in gaining promotion without their manager's support.¹⁰

On average about 20% of employees are nominated per cycle. The committee makes decisions on the basis of three primary sources. The first source is a collection of letters of evaluation from peers and managers. The promotion candidate and his manager can decide who these evaluators are. The second source is a statement by the candidate, outlining his or her accomplishments and case for promotion. The third source is the employee's history of numeric and written performance reviews.

The numeric performance scores were not mechanically linked to promotion decisions through a rigid, inflexible formula.¹¹ Nonetheless, these subjective performance metrics represent the closest empirical analogue to the "scores" used in Siegel (2009) and other contest theoretic models to select winners and losers in tournaments.

Company policy requires that at most 10% of all workers be promoted. In the data, the 10% figure is exactly realized nearly always. This policy is the basis for the characterization of the incentive scheme as a contest or tournament.¹²

⁹For each combination of job level and type, the firm published descriptions of expected responsibilities and contributions for employees to review.

¹⁰This paper does not include data about nominations or their sources, so I cannot report how many.

¹¹In other settings, companies have implemented a formulaic relationship between subjective performance scores and promotion contests. For example, Carlson's 2014 account of Yahoo's employee ranking system says that, "Eligibility for bonuses, promotions, and transfers within the company would be based on their average score for the past four quarters. [...] Under the new system, the only way to get a promotion or raise at Yahoo was to have an average score of three for the past four quarters."

¹²I interviewed managers at the firm to question the characterization of these incentives as contests. Given several potential shortcomings of tournaments, would the firm truly create a contest-like promotion system? "These are most definitely contests," said one HR representative.

Why did the firm organize a tournament? In interviews with managers, the main reason provided was a concern about collusion between middle managers and employees. “If we didn’t limit promotions,” said one HR professional, “Then managers would simply promote everyone, as a means of buying the cooperation and loyalty of their workers at the expense of the company.”¹³ In addition, some employees mentioned the simplicity of a 10% rule. This required only that managers involved in promotion decision simply rank the promotion candidates and select the top 10%, rather than decide both the threshold and ranking (or making compensation decisions for each employee).

Table 2 describes the relationship between performance scores and promotions. All regressions are linear probability models of the promote/not decision. In Panel A, we see that worker fixed effects and tenure controls alone have a large explanatory power over promotion decisions. With both sets of fixed controls included and nothing else, R^2 is 0.37.

In Panel B, we see the role played by the subjective performance scores. A single standard deviation increase in subjective performance in a given quarter increases the probability of promotion by 5%. Performance scores from prior quarters are also positively correlated with performance scores. However, once worker fixed effects and tenure controls are included, only the most recent performance score has significant weight.¹⁴

Table 2, Panel C compares two transformations of the performance score. The first is a normalization of the performance score, and the second is the percentile rank of the scores. Contests and auctions are decided by discontinuities in ranks, and indeed the percentile version of the regressions have the highest explanatory power. This is particularly true when the regression includes a dummy when an employee’s score is above a certain percentile. A flexible algorithm chose the 87th percentile as the likely location of a kink. This is very close to the threshold of 90% implied by the firm’s institution of promoting 10% of workers per cycle.

These findings are consistent with the characterization of the firm’s promotion system as a tournament in which the top 10% are rewarded with promotion. In the final panel D, we see results about the scope of comparison in promotion decisions. Performing well compared to employees within the same business unit is a significant predictor of promotion. However, there is additional predictive power of performing well compared to local peers who have the same manager.

The remainder of this section discusses how common promotion systems like this firm’s are (2.1) and a few comparative features of the firm’s model (2.2).

¹³This differs from the standard reason for relative performance evaluation, which was to remove common productivity shocks (Green and Stokey, 1983).

¹⁴Table 2, Panel B looks only at the first lag, but similar qualitative results exist for the second, third and fourth lags.

2.1 How common are workplace tournaments?

How common are contest-like systems for promotions, raises and other real-wage increases? The consensus among economists and business scholars appears to be that workplace tournaments are widespread.¹⁵ The practice of workplace competition has several high-profile advocates in business¹⁶ who refer to the practice using various nicknames.¹⁷ A list of well-known firms currently or previously using tournaments (according to journalistic and academic sources) is reported in Panel B of Table 1, and includes a mix of old- and new-economy firms.¹⁸

Despite the growing theoretical and empirical literature about contests – much motivated by workplace tournaments – data on the abundance of promotion contests is rare. No paper attempts to measure the empirical prevalence of contests as employee incentives.

This paper attempts to fill that gap in that data by conducting two surveys of over 15K Americans. Results (reported in Table 1) suggest that “Performing well compared to peers at job,” is the most common reason for a real-wage increase, and is almost twice as common as earning a real-wage increase from leaving for a new employer, enjoying a market wide wage increases or asking an employer to match an outside offer.

The results also suggest that over 77% of Americans work in a company with a tournament-like system of promotions that feature restrictions on the number of candidates who can be promoted.

2.2 Important Details and Comparisons to other firms’ tournaments

An important detail of this firm’s tournament system are the consequences for employees in the bottom of the distribution. At Microsoft, Enron, GE and many other firms using contests (see Section 2.1), low-ranking employees were subject to harsh punishment such as dismissal, demotions or sometimes pay reductions.

¹⁵For example, Prendergast (1999) writes that promotion tournaments are, “Perhaps the most common means of rewarding white-collar workers for effort,” and asks “[W]hy are they so popular?”

¹⁶This includes former CEO and Chairman Jack Welch, Former Microsoft CEO Steve Ballmer, current Yahoo-CEO Marissa Mayer, Enron executives Jeffrey Skilling and Kenneth Lay as well as executives at McKinsey & Co. (Michaels et al., 2001).

¹⁷For example, the tournament systems are sometimes called “rank-and-yank” (Gladwell, 2002), “force-rank” (Blume et al., 2006), “stack-ranking” (Eichenwald, 2012), “the vitality curve” (Welch and Byrne, 2001), “differentiation” (Welch and Byrne, 2001), “the 70/20/10 rule” (Welch and Byrne, 2001), “performance review committee” (Thomas, 2002).

¹⁸Because of negative publicity from media stories such as Eichenwald’s 2012 study of Microsoft’s promotion system, some firms are now denying the use of “yank-and-rank” or claim to have abolished it. The author has investigated, and it appears that these firms have not entirely abandoned rank-based incentives. Instead, they have weakened the incentives at the bottom of the distribution, for example, by no longer automatically firing the lowest ranking workers and providing a weaker punishment instead. Meanwhile, incentives at the top of the distribution remain strong and provisioned by rank-based methods. As discussed in Section 2.2, this distinction makes no difference for the behavioral predictions of standard contest theory models.

By comparison, consequences for low-ranking employees in this paper were milder. Such employees were denied wage growth, income and career opportunities. Low rankings could have reputation effects, particularly because the ranking would become part of the employee's permanent personnel record that can be viewed by future managers at the firm. However, workers were not automatically fired or reduced in pay. Some workers were able to recover from low rankings. [Carlson \(2014\)](#) writes of Yahoo, "Employees ranked poorly would see their lives materially turn for the worse as they lost out on raises, promotions, and bonuses. [...] Employees with low enough scores would be asked to leave the company."

From the lens of standard contest theory models, framing rewards as gains or avoided losses makes no difference. The theoretical predictions regarding effort, sabotage and other variables are the same however the problem is framed, so long as utility is distributed via the tournament mechanism. However, journalistic accounts of Microsoft and GE's method by [Eichenwald \(2012\)](#) and others suggest these punishments were especially motivating, possibly because of loss aversion ([Kahneman and Tversky, 1984](#)). We discuss our results in light of this difference in the conclusion (??) of this paper.

A second detail is that the 10% budget is within business units consisting of workers of many different ranks and types. This system creates competition between dissimilar employees for promotion slots, such as junior and senior employees. Although lower level employees face lower performance expectations, the firm's institutions place them into competition with senior employees through the 10% quota. A high-performing senior employee may face competition from high-performing junior employees even if he out-performs his other senior colleagues.¹⁹

3 Identifying a Causal Effect of Competition

Despite creating a contest for promotions, the firm paid little attention to contest-theoretic issues when assigning workers into larger departments and teams. The firm did not make a conscious decision to aggregate workers into units based on optimal levels of intra-worker competition.

Doing so would have been very hard to achieve, even had the firm attempted it. Many of the firm's employees were new, and the firm lacked much experience with these employees to use as the basis for an optimal match for a new employee (about whom it knew even less than the current employees).

Interviews with the human resource professionals confirm that contest-theoretic issues – even informally understood – were not the basis of consideration for the formation of business units.

¹⁹This is not only an issue in theory – one senior employee interviewed discussed concern about his own prospects based on the strong performance of junior employees.

These issues were ignored both with regards to initial unit assignments as well as reorganizations. By contrast, matching decisions were made somewhat haphazardly. A discussion of how and why the firm (and its recruits) would accept such haphazard matching follows later in this section.

A common way of assigning new employees to units at the firm was based on date-of-hire. In this method, the firm assigned employees in batches on certain days. Workers were given wide latitude to select the timing of arrival, and the timing was generally affected by landlord, spousal, vacation and relocation-related preferences. The mapping of dates to business units was unknown to the firm itself until a few days in advance.

As such, similar employees who arrived in slightly different dates would be assigned to different units and different contemporaneous (and future) competition. Even if competition dynamics were perfectly observable and predictable, this mechanism made it very hard for employees to strategically time arrival to join a particular group. The discussion and analysis of identification in Section 5.2 shows that arrival date was indeed a strong predictor of unit assignment.

We see very little evidence of selection, or workers endogenously conspiring to manipulate assignments. As discussed below, predicting worker performance is difficult and would be necessary for strategic matching on the basis of contest considerations. However, to account for undetectable types of endogeneity, the results in this paper include instrumental variable specifications attempting to identify estimates from the date-of-hire variation. The resulting estimates are not qualitatively different than the OLS results, and the estimates' confidence intervals mostly overlap.

The remainder of this section discusses the practice of assigning workers to business units based on the date-of-hire. Why would a firm organize itself this way (3.1)? And why would job candidates agree to job offers with uncertain assignments (3.2)?

3.1 Reasons for the firm's assignment mechanism

It may seem odd that the firm attempted so little optimization of employee assignments. A rudimentary attempt at optimal matching could improve welfare for both the firm and its workers. If workplace competition indeed has the effects documented in this paper, it is strange that the firm wouldn't try to exploit them more directly through contest design.

A rudimentary form of optimal matching could also improve welfare for candidates, and thus the firm's recruiting. In many companies, job candidates know their potential destination inside the firm at the time they accept/reject a job offer. However, to quote from an internal document from the firm, "Candidates were hired into [*Company*] without knowing their intended project focus."

There are several reasons for the firm's assignment institution. We discuss a few below. The first

reason is that the firm's HR function was capacity constrained. The firm was growing rapidly in nearly every department except HR. The firm lacked a mechanism for performing the match, that didn't involve HR employees reading resumes and attempting a match.

The firm's and industry's fast growth created other problems for optimizing matching. The company's executives were philosophically opposed to "overfit" job assignments. They anticipated technological change in the product market that would change demands on employees' work.

The resulting recruiting and hiring strategy placed a heavy emphasis on general human capital, rather than task-specific human capital. This emphasis was meant to avoid "overfit" candidates who may have been a great match for current needs in a particular department, but who may have been unable to adapt. Hiring was therefore centralized. The centralization was meant to remove hiring from the hands of business units, who were likely to hire based on short-term rather than long-term needs. This philosophy is not uncommon in the technology industry. For example, a management book by Google executives [Schmidt and Rosenberg \(2014\)](#) says, "The urgency of the role isn't sufficiently important to compromise quality in hiring."

This is clearly not a firm that believes strongly in the benefits of optimal short-run matching of employees to business units.

Lastly: Organizing workers into optimal contests would be hard to implement for reasons anticipated by the employer learning literature ([Kahn and Lange, 2014](#); [Radner, 1992](#)). Organizing workers optimally would have required advanced knowledge of the long-term career trajectories of employees at the time of hire and assignment. This would be difficult under any circumstances, but especially because the firm's production technology was new and different than others' in the industry. As such, inferences made on the basis of past performances would have been less robust.²⁰

Nonetheless, this firm repeatedly attempted to make these inferences through analysis of employees' interview scores (taken from the time of hire) with realized performance on the job after being hired (measured by subjective performance scores and other metrics). Working independently and together, the firm's own statisticians were unable to find any robust relationship. Outside statisticians were also consulted and were also unable to find a predictive relationship.

An executive from the firm's industry discussed similar research findings in a *New York Times* interview in 2013 ([Bryant, 2013](#)), saying:²¹

"Years ago, we did a study to determine whether anyone at [our company] is particu-

²⁰The relationship between technological change, obsolescence and labor markets is a well-chronicled issue in the technology industry. See, for example, [Brown and Linden \(2009\)](#).

²¹URL for interview and article: <http://www.nytimes.com/2013/06/20/business/in-head-hunting-big-data-may-not-be-such-a-big-deal.html?pagewanted=all>. Last accessed October 24, 2014.

larly good at hiring. We looked at tens of thousands of interviews, and everyone who had done the interviews and what they scored the candidate, and how that person ultimately performed in their job.

We found zero relationship. Its a complete random mess[.]”

These findings are consistent with a large literature in industrial psychology summarized by [Macan \(2009\)](#), which show the low- or non-existent predictiveness of interviews on job performance.²²

The imperfection of employer learning and predicting employee quality has also been a theme in economics. Slow employer learning is a leading hypothesis for the correlation between wage dispersion and age/experience. According to this line of research, wage dispersion increases with tenure because employers need time to distinguish high- and low- talent employees.

This literature suggests that the employees in this study have exactly the age and experience profile that would make them most difficult to organize into optimally designed contests.

Employer learning is further made difficult because employee productivity evolves over time. [Kahn and Lange \(2014\)](#) summarize and extend this literature, finding that employer learning continues throughout the life cycle and that, “Imperfect learning [...] means that wages differ significantly from individual productivity all along the life-cycle because firms continuously struggle to learn about a moving target in worker productivity.” This would make organization into optimal contests hard, even for higher-tenure employees.

Firms’ struggle to estimate worker productivity is, in some sense unsurprising. At their core, worker measurement issues are causal inference questions (“How much did worker X ‘cause’ outcomes to improve?”). Firms rarely create experiments necessary for causal inference at an individual-level. Even if they did, they would often lack statistical power due to the extreme noisiness of outcomes.²³

For example, some economists have suggested sales as a white-collar job whose output can be easily measured in dollars. However, most firms do not experimentally rotate salespeople to measure the causal effect of individual salespeople. Furthermore, many firms assign entire teams of salespeople to important clients, thus confounding the measurement problem.

Even if firms ran such experiments, sales data is extremely noisy. [Lewis and Rao’s 2012](#) study of advertising shows that even optimally-designed sales experiments would lack statistical power and fail to produce useful standard errors. In a labor productivity context, [Barankay \(2012\)](#) men-

²²[Macan \(2009\)](#) reports particularly poor results for “unstructured interviews,” in which interviewers are relatively free to lead the discussion in any direction. The firm in question used unstructured interviews.

²³Team production also complicates measuring individual-level talent.

tions the large variance in sales performance as an obstacle to designing experiments with firms.²⁴

3.2 Reasons the uncertainty in assignments was acceptable to job candidates

For my instrumental variables approach, I show in Table 4 that employees would not have known what start date would get them assigned to more or less competitive groups. Variables in Table 4 known at the time of hire are uncorrelated with my instrument.

A separate question is why a worker would agree to join a firm without more details about his/her job assignment. During the sample period, the firm enjoyed a strong reputation as an employer, and experienced positive balance sheet growth.

As such, the firm was able to recruit effectively without making promises about job destinations. One example of this strategy came from Facebook COO Sheryl Sandberg. In 2012, Sandberg told Harvard Business School graduates the story of her recruitment to Google in 2001. She discussed her unease about the role she was offered, and Google CEO Eric Schmidt allegedly replied:

“Don’t be an idiot. [...] If you’re offered a seat on a rocket ship, don’t ask what seat. Just get on.”

Sandberg forwarded this advice to the Harvard graduates at her speech.²⁵ The strategy worked well for Sandberg, who accepted the Google’s offer and was a sales executive from 2001 to 2008 during a period of strong growth.²⁶

She became a multibillionaire in Facebook’s 2012 IPO. Sandberg and Schmidt’s stories provide evidence of how and why job applicants may accept ambiguous job offers in order to join firms with strong reputations and growing balance sheets. Schmidt summarizes:

“When companies are growing quickly and they are having a lot of impact, careers take care of themselves. And when companies aren’t growing quickly or their missions don’t matter as much, that’s when stagnation and politics come in.”

²⁴Barankay (2012) writes, “For reasons of statistical power, I had to span the experiment due to the large variance in sales performance: As I wanted to be able to test the difference across treatments and by gender, I could only have three treatment groups per year to achieve the required statistical power.”

²⁵Text of the speech: <http://www.businessinsider.com/sheryl-sandbergs-full-hbs-speech-get-on-a-rocketship-whenever-you-get-the-chance-2012-5>.

Video of the speech: https://www.youtube.com/watch?v=2Db0_RafutM.

Both last accessed October 24, 2014.

²⁶She later repeated the strategy. In 2008 Sandberg turned down offers to become CEO of other companies (including *The Washington Post*) to accept a COO job, reporting to a 23-year old. She once again accepting restrictions and uncertainty on her responsibilities and job title in order to join a faster-growing firm.

4 Data

The data from the firm includes roughly 60,000 workers over the period of 2000-2009. The workers are mostly sales and engineering staff who have a high level of education. The median salary is over \$100,000 per year.

For the analysis in this paper, I organized the data into a quarterly panel of individuals. Unless otherwise stated, the variables below are aggregated at the individual \times quarter level. I organize this section into three sections: Competition measures (4.1), outcome measures (4.2) and controls (4.3).

4.1 Measures of Competition

The objective of this paper is to measure how changes in competition for promotion affect worker behavior. As such, measuring the level of competition intelligently is important. Unlike hard information such as lines of code written or reviewed, competition represents a more abstract and amorphous concept to be handled circumspectly. Rather than viewing a single competition measure as “right,” and the others as wrong, a comprehensive approach seems more fruitful and convincing. Below, I describe my preferred measure of competition. However, recognizing the potential for disagreement, Appendix ?? reproduces the analysis with several plausible alternatives. These other measures produce the same qualitative results, so little of what follows hinges on the the quirks of this specific measure.

The primary measure of competition used in this paper is derived from subjective performance scores of workers in the previous quarter. Employees whose peers score similarly are coded as facing high competition, and employees whose peers score very differently (either higher or lower) face lower competition.

A formalization follows in Equation 1. I will first offer a defense of this measure motivated by the literature on formal contest theory models. These models feature a collection of rivals, each with a parameter representing their talent (or other form of advantage) that affects their odds of winning. Workers then choose effort and create output, which is observed with noise.

In this setup, homogeneity in the odds of winning (through equal talents or other handicaps) motivates effort. In a battle between unequal rivals, neither has any incentive to work. The stronger will prevail with minimal effort, even if the weaker supplies maximal effort. Seeing this in advance, neither side chooses to work. By contrast: If rivals are roughly equal, then the returns to effort are greater and thus agents supply more of it.

My measure of competition is thus based on subjective performance scores, which are analogous

to each employee's ex-ante probability chance of promotion. As discussed in the institutional details (Section 2), subjective performance scores are closely tied to promotions. This is shown in the data in Table 2. One of the primary reasons the firm scores candidates is to guide the promotion decision. The performance score can be interpreted as an employee's proximity to promotion.

To measure competition, I thus calculate how much each focal worker is equidistant to promotion compared with his/her peers. If they are equidistant, and if only a finite number can be promoted, then this would place the peers into greater competition with each other. At equidistance, an increase in effort would have a greater impact on the probability of success than if peers are disperse for the reasons discussed in my example above.

The measure is formally defined below. An employee i working in business unit j in period t would face competition defined as follows:

$$x_{i,j,t} = -1/N \sum_{k \in j, k \neq i} |PerformanceScore_{i,t-1} - PerformanceScore_{k,t-1}| \quad (1)$$

... where $k \in j, k \neq i$ refers to the other workers in unit j besides i . This formula codifies the concept of the average absolute distance in the previous quarter between an employee's subjective performance score and those of his or her contest rivals.

I use a lagged measure in order to capture the competitive standing at the last time the firm formally scored candidates before choices are made in the current period. Would workers know their competitive standing? I address this question in 4.1.2, below.

Using the specification in Equation 1, a low distance implies lots of close competition and strong incentives. A high distance implies little competition or incentives.

The rest of this section proceeds as follows. First, I compare my measure of competition and incentives with a few others used in the empirical contest literature. Next, I discuss how workers might know their competitive standing (4.1.2). Lastly, I discuss measurements of counterfactual competition (?). This measure of counterfactuals will assist in the instrumental variables strategy discussed in Section 5.2.

Lastly, several alternative measures of competition are also possible based on job levels and other functions of performance scores. I study these for robustness, and these are defined and discussed in Appendix ??.

4.1.1 Comparison to Other Measures of Contest Intensity

Much of the extant empirical work on contests exploits naturally occurring or experimentally induced variation in prize structure or prize allocation rules. By contrast, variation in incentives in this setting derives from changes in the composition of contestants.

In the empirical contest literature, various other variables have been used to measure the strength of competition and incentives. One common measure of incentive strength is to utilize variation in the size of the contest prize (Garicano and Palacios-Huerta, 2005; Ehrenberg and Bognanno, 1990).

Rather than studying variation in contest size, this paper studies variation in the composition and relative strength of opponents. In this way, the paper is similar to Brown's 2011 study of contestants in golf tournaments. However, my measure is different from Brown's 2011 competition variable in that Brown (2011) was entirely about the presence or absence of a single superstar contestant (Tiger Woods). This is partly because Brown's 2011 paper is motivated by a different research question regarding superstar effects. Even within the setting of professional golf, it is clear that incentives can also come from the proximity of non-superstar opponents who may be able to offer competition. This is true in a workplace setting as well.

In addition: In a workplace setting, single superstar opponents are less important sources of competition. This is because the contest allocates more than one identical top prize (in our firm's case, 10%). This widens the space for the competitive influence of non-superstar opponents. In fact, the strongest competition may be in fact near the 10% percentile threshold – very far from Brown's 2011 elite swinger.

4.1.2 Do Workers Know their Competition?

A necessary condition for competition to motivate is that workers know the degree of competition they face. A worker knows his or her own performance but is not privy to the performance ratings of others, so these must be inferred. Is such inference likely, or even possible?

Workers have many ways in which to evaluate peers' performance and relative positions. Since expectations and accomplishments are often announced, acknowledged and celebrated at regular meetings and shared informally, workers know who contributed significantly within their team. Such "wins" are key drivers of performance scores.

Many of these accomplishments directly affect the work of other peers. Thus it is not possible to hide significant accomplishments or lack thereof. If a software engineer develops a new feature for his/her product, other engineers will have to interact with that engineer and his feature in order to integrate it. In the process, these peers will be able to observe the quality of the contribution and

how it was received by its consumers. Similar dynamics exist in a sales context. If a salesperson has recruited a large client, others will be assigned to that client to assist in the additional work of servicing the account.

In addition, the firm has a system of quarterly tactical planning in which quantifiable goals and deadlines are set in unit-wide meetings along with owners. Explicit performance expectations are set in these meetings. For example, the minutes of one such meeting include the statement: “By January 2003, we aim to launch a feature codenamed XYZ that will enable clients to accomplish X with a single click. [Employee Names] are in charge of this implementing and launching this feature by January 2003.”

These goals are quantitatively scored afterwards in similar unit-wide meetings. While not identical to performance scores (since they are scored by goal rather than by individual), they are nonetheless indicative of the responsible individual’s standing among his peers.

There are other direct ways to evaluate peers’ performance. As discussed in Section 4.2, the “objective” performance data in this paper are taken from internal production infrastructure. These systems log worker activity mainly to facilitate followup, debugging, collaboration and auditing by peer workers.

Workers may readily observe these measures of peers’ activity. Although they may not directly know how these measures are interpreted by management, this does give additional insight into how competitors are performing. Regressions in table X show that these “objective” measures are correlated with subjective performance and promotion outcomes.

A final way that employees know their relative standing is through direct sharing and discussion. Anecdotal and interview evidence suggests that workers discuss impressions of colleagues’ career prospects, and sometimes share private information about their own evaluations. Such discussions are much like those that Lewis (1989) describes as common in the finance industry.

The setting is not unlike academia: Although formal feedback on tenure progress is private, colleagues can form impressions based on publicly available signals. These may include conference and/or journal acceptances, editorships, refereeing, conferral with others and direct evaluation of research and teaching. In addition, some colleagues share their private information in ways that partially or fully reveal competitive standing information.

4.2 Outcome Measures

The most novel data in this paper are the variables relating to the many dimensions of productivity and effort. The nature of production at this firm generates a large amount of data. Employee use of the firm’s production infrastructure is often tagged and timestamped with worker-identifying

information. The firm logs this data primarily for debugging and followup purposes,²⁷ and not for performance evaluation.²⁸

My data includes roughly 18 measures of output from the activity logs. Below, I give a sample of outcome measures for the two most common job categories (software engineers and sales/marketing professionals). The full set of underlying variables are described in detail in Appendix ???. Next, I itemize how these measures are summarized into measures of interest to the literature.

For software engineers, important measures of productivity include lines of code submitted or changed in the repository, the amount of compiles and the number of code reviews performed for other employees. For sales and support staff, important variables include data how often each employee contacts clients, and how often employees perform small tasks for clients such as reviewing and approving requests for account changes.²⁹

These underlying variables are summarized into into several outcome measures in a worker \times quarter granularity. These are generally the dependent variables in regressions described in Section 5. These variables are discussed below.

4.2.1 Output and Effort

Dating back to Lazear and Rosen (1981), economists studying contests have primarily focused on “choice of effort” in theoretical and empirical research (CITES). We measure these choices in the following way.

Hours Worked. As previously mentioned, use of the company infrastructure is often logged with worker-IDs and timestamps. To measure hours of work, I count unique hours with a timestamp.

This measure has two benefits compared with typical measures of working hours used elsewhere. First: It is not-self reported. Second, it does not include working hours in which the worker may be physically at work but not doing anything.

This measure no doubt excludes some productive activity while at the firm that cannot be logged. To control for the possibility that these holes in the data affect some groups differen-

²⁷For example: Additions and modifications to the firm’s software corpus are tagged and timestamped. Through this setup, managers and employees are able to identify the original authors of code or documents that need followup. The firm’s production systems (such as its software compilers) also track usage. Should one of these systems temporarily break, these logs are useful for debugging.

²⁸The firm’s employees and managers are opposed to using much of this data for performance evaluation because of the possibility of gaming. Using the example in the previous footnote: If the firm evaluated performance based on lines of code contributed to the codebase, then employees would have incentive to contribute lengthy, inefficient code.

²⁹For both of these measures for the sales staff, there is enough demand for this labor such that workers never run out of tasks.

tially, my econometric specifications include fixed effects for individual workers, time-periods, job types, job levels and business-units.

In addition, in some specifications I measure hours as the difference between each day's first and last hour in local time. When this version of the variable is used, it is noted in the table.

Total Output. Total output is measured as the sum of all activities across all productivity dimensions. To ease interpretation of coefficients, I standardize the variable in regressions by subtracting the mean and dividing by the standard deviation. To account for certain jobs and business units working more on particular activities, my specifications include worker-, job-level-, job-type- and business-unit fixed effects. Additional detail on these specifications is in Section 5.1.

4.2.2 Efficiency and Quality

Promotion contests have been criticized for encouraging "influence activities" (Milgrom and Roberts, 1988; Milgrom, 1988, Gubler et al., 2013) rather than productivity. An example of this comes from Eichenwald's 2012 journalistic account of Microsoft's promotion system:³⁰

"The best way to guarantee a higher ranking, executives said, is to keep in mind the realities of those behind-the-scenes debates— every employee has to impress not only his or her boss but bosses from other teams as well. And that means schmoozing and brown-nosing as many supervisors as possible."

Similarly at Enron, Bodily and Bruner's 2002 writes that "[R]ank-and-yank turned into a more political and crony-based system." Carlson (2014) of Yahoo, "As employee ratings got passed up the management ladder, individual scores sometimes had to be adjusted at the department level so that the right amount of employees were in each bucket. This led to favor trading between managers. It also meant that employees felt they had to brownnose their boss' peers and their boss' boss."

Even if workplace competition increases worker effort, much of that effort may go into lobbying and influence activity. As Eichenwald (2012) describes Microsoft:

"I asked Cody whether his review was ever based on the quality of his work. He paused for a very long time. 'It was always much less about how I could become a better engineer and much more about my need to improve my visibility among other managers.'"

³⁰ <http://www.vanityfair.com/business/2012/08/microsoft-lost-mojo-steve-ballmer>

In the data, such activities would appear as decreases in per-hour efficiency or quality. Hence, I address these hypotheses through the following variables:

Efficiency: The ratio of output to hours. This is also reported in normalized terms. Regressions with efficiency as the outcome variable include controls described above.

Quality: The amount of code submitted to the code repository that was subsequently, in future periods, withdrawn or reverted because of problems or bugs discovered in the code.

4.2.3 Cooperation and Sabotage

Promotion contests also potentially create incentives for sabotage and other forms of anti-social behavior, as well as discouraging productive cooperation between employees. This possibility has been much studied theoretically (Dye, 1984, Lazear, 1989 and Rob and Zemsky, 1997), and memorably dramatized in the fictional real-estate sales tournament in *Glengarry Glen Ross*. While David Manet's play illustrates an extreme form of sabotage, more subtle forms of sabotage seem to be common at some companies. For example, Eichenwald (2012) writes of Microsoft:

"Staffers were rewarded not just for doing well but for making sure that their colleagues failed. As a result, the company was consumed by an endless series of internal knife fights. [...]"

People responsible for features will openly sabotage other people's efforts. One of the most valuable things I learned was to give the appearance of being courteous while withholding just enough information from colleagues to ensure they didn't get ahead of me on the rankings."

Similarly, Carlson (2014) wrote that at Yahoo, "Workers would prioritize tasks that got them closer to their personal goals over doing anything else. This made sense. Collaborating and helping out on a project that wasn't going to get you close to an 'exceeds' was just a stupid thing to do."

The empirical literature on sabotage has mostly taken place in labs (for example, Carpenter et al., 2010; Harbring and Irlenbusch, 2011). The rare exceptions from outside the lab include studies of professional soccer by Garicano and Palacios-Huerta (2005) and judo by Balafoutas et al. (2012). Drago and Garvey (1998) use survey data from Australian manufacturing to shed some light on cooperation – the survey results show that when promotion incentives are strong, workers are less likely to provide "helping" behavior such as allowing others to use their equipment.

In this paper, we lack direct measures of sabotage. However, we have several measures of productive cross-worker cooperation and collaboration. These are:

Peer bonuses. Employees at the firm are able to reward each other with roughly \$200 bonuses for excellent, otherwise unseen or unrewarded contributions or assistance. These rewards are accompanied by a laudatory email to the recipient’s manager and sometimes the executive and/or entire group. The outcome metric used in my regressions is the number of peer bonuses received by each employee in each quarter.³¹

Writing documentation. Inside a software company, documentation of the firm’s infrastructure is an important facilitator of collaboration and teamwork between employees. Using documentation, a software engineer can quickly gain the knowledge necessary to contribute to a co-worker’s project.

4.2.4 Innovation

Incentives for innovation are also a longstanding theme in the contest literature. One of the primary applications for contests to encourage innovation (for example, [Baye and Hoppe \(2003\)](#) and [Fullerton and McAfee \(1999\)](#)). A related literature shows the power of specially-designed contests for innovation and research (see for example [Boudreau et al. \(2011\)](#)).

In theory, incentives based on output might give employees incentives to invest in projects. In a slightly different context, [Aghion et al. \(2005\)](#) discusses the “inverted U-shaped” relationship between competition and innovation, with an interior optimum.

However, the same factors that lead workers to produce “influence activity” instead of productive output may also lead them to eschew innovation in favor of more visible forms of output. [Azoulay et al. \(2011\)](#) show that weaker incentives allows longer term investment that fosters high impact and creative work. As stated in [Eichenwald’s 2012](#) account of Microsoft’s promotion system:

“[B]ecause the reviews came every six months, employees and their supervisors who were also ranked focused on their short-term performance, rather than on longer efforts to innovate.”

To address this topic, our data contains many measures of innovation.

Patenting: Employees at the firm are rewarded bonuses for submitting ideas that lead to a patent application. Most of these applications lead to a patent, but the evaluation process at the government usually takes several years. This data on patenting productivity data comes from the firm’s internal record of who made the patents.

³¹My data does not specify who the bonus was from. Although it is possible for peer bonuses to be given to worker from someone outside of his or her set of contest opponents, the firm says this is relatively rare.

Contributions to ideas board: In order to solicit and evaluate new product, business and feature ideas, the firm created an internal “ideas board” to collect innovative proposals from employees. This application was accessible via a web browser, and allowed employees to suggest new ideas and receive ratings and feedback on them. I include not only the number of these ideas as an outcome variable, but also their average rating.

4.2.5 Specialization and Differentiation

Specialization and differentiation are relatively unstudied aspects of the literatures on contest theory, organizations and specialization. However, the relationship between incentives and specialization is discussed somewhat in [Holmstrom and Milgrom \(1991\)](#), and in a variety of other analogous setting such as [MacDonald and Marx \(2001\)](#).

My calculation of worker specialization uses the a formula for the Herfindahl-Hirschman Index (“HHI”) from the IO literature on market concentration ([Hirschman, 1945](#); [Herfindahl, 1950](#); [Hirschman, 1964](#)).³² The formula is below.

$$Specialization_{i,t} \in (0, 1] = \sum_{l \in L} s_{l,t}^2 \quad (2)$$

... where $s_{l,t}$ refers to the share of the worker’s total activity counts from activity in dimension l , and L refers to the set of all dimensions/activities.³³ The variable is has an upper bound of 1, representing complete specialization into one activity.

For differentiation, I create a measure of how similar workers’ outputs are to each other. To implement this, I represent each worker’s productivity as a point in multidimensional Cartesian space, and measure the average distance between the focal employee and his or her contest opponents. My preferred measure of distance is Euclidean, although many alternative measures are possible.³⁴

$$Differentiation_{i,t} = \frac{1}{N} \sum_{j \in J} \sqrt{\sum_{y \in Y} (p_{i,t,y} - p_{j,t,y})^2} \quad (3)$$

As with the variables above, these variables are normalized to ease interpretation. Regressions include controls to account for different roles. Alternate measures of specialization or differentia-

³²The measure is known as the “Simpson index” in population biology ([Simpson, 1949](#)) and is known as the “participation ratio” in physics ([Eliazar and Sokolov, 2010](#)).

³³For example: Suppose a worker performed 4 total activities activities in a month. One of the activities was a code review, and the other three were patents. This worker would have a specialization score of $0.625 = 0.25^2 + 0.75^2$.

³⁴Results from alternative definitions are available by email.

tion produce very similar results.

4.2.6 Sorting and Selection

Finally, an important function of contests is selection and sorting. The nature of competition may not only effect how hard employees work, but also whether and where they choose to work at all.

The limited theoretical research on this by [Morgan et al. \(2012\)](#) shows that in large contests, high-types clustering together, despite the stiffer competition. However, this contradicts the intuition that high types will want to separate in order to mitigate competition, and thus each become the “king” of a smaller, local hill. [Morgan et al. \(2012\)](#) shows this behavior is possible.

The selection and sorting aspects of workplace competition are an important practical consideration in contests. [Carlson \(2014\)](#) writes of Yahoo:

As 2013 rolled on, Mayer’s system made life particularly difficult for Yahoo’s middle managers. It was hard to get talented people to work in the same group. Not only did people not want to compete against other talented employees, they also worried that if they transferred in the middle of a quarter, they’d whiff on their goals, get a mere “achieves [expectations, a type of rating],” and lose out on a chance for a raise anytime in the next twelve months.

My primary measure of sorting decisions is quitting, which I can measure for all workers as well separately for different levels of subjective performance scores.

4.2.7 Subjective Well-Being and Job Satisfaction

The final set of outcome variables comes from a confidential job satisfaction survey asked by the firm’s HR department. This happens only once in the middle of our sample, and is only available for a subset of employees who answered the firm’s survey. The survey generally measures satisfaction with the company, one’s job and manager and peers.

4.2.8 Use of the Outcome Measures by the Firm

The activity logs I use for measurement are common practices in software engineering and other knowledge-based work. Such logs are proliferating as more production takes place through remote “cloud” servers, even for word-processing and other non-engineering tasks. For software engineering, these logging features are offered in the most popular version control systems and

are used throughout the software development industry. Other scholars (for example, [Lerner et al., 2006](#)) have used similar data on code contributions to study the economics of open source software communities.

Workers in these industries generally know that their productive activities are logged for debugging and auditing purposes. In interviews at this firm, workers did not consider this logging as performance measurement at all, but rather as useful productivity, development and coordination tools for an inherently team-based production environment. Much of the logging is deliberately made available to other workers at the firm in order to assist collaboration. For a given piece of code or document, it is easy to see who altered which parts and when. In theory, workers could compile these logs into the daily aggregations about each other, but this would require considerable additional effort without any clear benefit.

Importantly, this data is generally not used for performance evaluations and never contracted upon. In fact, most of this data was in fact created and systematically compiled by this author for this research agenda.

The idea of using these metrics for performance evaluation is generally repugnant to workers, managers and HR executives in white-collar industries.³⁵ Incentivizing metrics such as “lines of code” or “documents edited” would create perverse incentives for inefficient writing and software.

Although the firm was not systematically aggregating this data, the metrics in this paper do capture aspects of performance that are observable to the managers. For example: Although the firm did not collect data about hours of work for employees at the firm, individual managers would be aware of it through direct observation. In Section X, I show that the measures I collected about worker effort and performance are predictive of subjective performance reviews and promotions.

4.3 Controls

Much of the data in this paper are typical personnel-economics variables from inside the firm. This includes the role, rank and salary of each worker. [Unfinished]

³⁵In [Cringely's 1996](#) 1996 documentary *Triumph of the Nerds*, Microsoft executive Steve Ballmer described IBM contracting on “lines of code” as a performance metric: “In IBM there’s a religion in software that says you have to count K-LOCs (and a K-LOC is a thousand lines of code). [...] IBM wanted to sort of make it the religion about how we got paid. And we kept trying to convince them - hey, if developer’s got a good idea and he can get something done in 4K-LOCs instead of 20K-LOCs, should we make less money? Because he’s made something smaller and faster? Less K-LOC? Ugh! Anyway, that always makes my back just crinkle up at the thought of the whole thing.” Ballmer’s animated retelling of this story appears in the the second episode of the series at 38:56 (https://www.youtube.com/watch?v=PWy1b_5I0w0&t=38m56s).

5 Estimation and Identification

5.1 Specifications

The specifications in this paper are panel data models with worker, period and business -unit fixed effects. The specifications take the following form:

$$y_{i,t} = \alpha_i + \delta_t + \gamma_j + \Omega c_{i,t} + \beta x_{i,j,t} + \epsilon \quad (4)$$

with:

y_{it} : Performance outcome by worker i at time t (see Section 4.2).

α_i : Worker fixed effect.

δ_t : Period-fixed effect (quarterly).

γ_j : Business-unit (contest) fixed effects.

$c_{i,t}$: Vector of additional employee and business-unit level controls.

$x_{i,j,t}$: Measure of competition faced by worker i in unit j at time t (see Section 4.1).

ϵ : Error term.

Standard errors are clustered at the business-unit level. The coefficient of main interest is β , which is predicted to be positive. Next I describe conditions under which the β coefficient from the specification above can be interpreted as causal and an instrumenting strategy.

5.2 Identification

As discussed in Section 3, assignments to units were strongly influenced by the date-of-hire. However, even without this source of variation, it may have been hard for employees or managers to conspire ex-ante to select levels of competition endogenously. This would require the ability to predict performance trajectories, which the firm (as well as the academic literatures) has found difficult.

Nonetheless, to account for unforeseen forms of selection, the results in this paper include instrumental variable specifications attempting to isolate variation from the date-of-hire variation. The resulting estimates are not qualitatively different than the OLS results, and the estimates mostly overlap.

A brief discussion of the empirical properties of the $x_{i,j,t}$ variable follows. Readers interested only in identification from the date-of-hire variation can skip to section 5.3 for the discussion of the that specification.

Brief discussion of $x_{i,j,t}$: Show that this variable is a random walk. Show that this variable is smoothly distributed. Show that the diff of this variable is smooth.

5.3 Instrumental Variable Approach

In this section I discuss the explicit use of time-of-hire based variation in an instrumental variables approach. This approach utilizes variation in the competitive pool created by the assignment mechanism which assigns workers to projects based on date of hire. To measure this variation using ex-ante characteristics, I use an instrument based on interview scores.

Creating an instrumental variable from the date-of-hire requires some additional work since time-of-hire affects employees differently. For “Worker B+,” arriving on January 5 rather than January 6 may have resulted in facing greater competition. For a different employee (“Worker B-”) – arriving early may have resulted in lower competition. For some employees, the arrival date would have made little difference.

I first show that the timing of arrival does influence project assignments. In Table 5 contains regressions of match realization. Each row in this regression is a possible match between an employee and a business unit. The dependent variable is a binary variable representing which matches were realized (assigned). The explanatory variables include interactions between worker characteristics (such as their job types and quarters of hire) and particular assignments.

The data show that these interactions do have explanatory power over assignments. Certain business units are hiring more in certain months. However, even on top of that – variables relating to micro-timing have explanatory power over assignment outcomes. For example: If assignments were based on hire-dates, then arriving on an odd or even day of the month would affect which business unit a new employee joined. As Table 5 shows, interactions between even/oddness of hire date and business-unit fixed affects have highly statistically significant explanatory power, measured by an F -test of these interactions.

I next define an instrument that effects $x_{i,j,t}$ (the measure of competition each worker faces). I create an instrument based on the level of competition implied by the average pre-hire interview scores for each employee and his/her contest opponents. To define this instrument, I first create a measure of competitiveness based on average interview scores. This is analgous to my measure of competition $x_{i,j,t}$, defined in Equation 1 – except it uses interview scores rather than performance scores.

$$x_{i,j,t}^{pre} = -1/N \sum_{k \in j, \neq i} |InterviewScore_i - InterviewScore_{k,t}| \quad (5)$$

To examine the causal effects of competitiveness on performance, we must calculate the counterfactual situation where individual i went to team k as opposed to her true assignment, team j . The measure in Equation 5 above permits this. These counterfactual estimates allow us to utilize econometric strategies that exploit differences in competition across groups, as a result of quasi-randomization of assignment.

From here, I create an instrument that measures the difference in x^{pre} caused by local differences in date-of-hire. Formally, the instrument is defined as:

$$z_{it} = \underbrace{1/N_K \sum_{k \in K} x_{i,k,t}^{pre}}_{\text{Average competition } i \text{ faces by joining one of the units that accepted workers on his hire date.}} - \underbrace{1/N_J \sum_{j \in J} x_{i,j,t}^{pre}}_{\text{Average competition } i \text{ would have faced by joining one of the other units that received workers in the surrounding two weeks.}} \quad (6)$$

... where:

- K refers to the set of units that received new workers of i 's type on the same day as i
- J refers to the set of units NOT in K that received new workers of i 's type in the surrounding two weeks.
- N_K and N_J refers to the number of units in of sets K and J , respectively.
- $x_{i,j,k}^{pre}$ calculated as in Equation 5.

This instrument is the difference in the realized $x_{i,j,t}^{pre}$ compared to the $x_{i,j,t}$ had the worker been counterfactually assigned to the units of similar workers who arrived in the two weeks surrounding his actual hire date.³⁶ This formulation exploits the fact that two workers with the same performance score may face different competition depending on peers.

The first stage of the IV is very strong, with an F -statistic of 30.71. This shows that there are meaningful differences in competition between contests generated by the assignment mechanism.

6 Results and Discussion

Table 6 presents normalized results on hours and output. We see a relatively large and statistically significant effect of the competition on overall effort and output. In Table 7, I show the effects of competition on the efficiency and quality of output. We see an increase in efficiency without effects on the quality of code. In Table 9, I shows effects on innovation, in which there are no statistically significant results in either direction.

³⁶Two weeks is an arbitrary restriction, and the results were generally robust to different windows.

Table 8: Effects on cooperation. This shows some truth to the concerns about sabotage. Table 11: Effects on quitting. These results are largely consistent with the existing literature. However, a large body experimental and field research in psychology suggests that incentives may actually undermine performance in tasks that require innovation or creativity. McGraw (1978), McCullers (1978), Kohn (1993), and Amabile (1996) suggest that incentives encourage repetition of past success strategies with greater effort, rather than exploration of novel untested ideas.

In my empirical setting, the core job responsibilities require some amount of creativity. Developing efficient software code, marketing plans and sales pitches are not “rote” activities akin to fruit-picking or athletics and instead require innovation and risk-taking. The results on my output measures in 6 contain many output measures that require creativity. Contrary to the aforementioned psychology, workers respond to contest incentives.

The variables in Table 9 (patents and ideas) attempt to isolate a few variables that particularly measure pure “innovation,” such as patenting and idea generation. Even in this setting – the outcomes most related to the psychologists’ theories – the effect of competition incentives is ambiguous.

Tournament incentives are also said to have negative side effects, particularly in the form of lobbying and sabotage (or decreased productive cooperation). I find some evidence of this in Table 8, which shows a lower level of cooperation and organizational citizenship between promotion competitors.

However, commentators and theorists discussing these negative side effects suggest that they may impact the efficiency or quality or output. In particular, effort spent on lobbying may detract time and effort from productive output. Similarly, sabotage and lobbying may harm the quality of output. My results on efficiency and quality in Table 7 suggest the overall effect on efficiency is strongly positive, and the effects on product quality can’t be detected.

In addition, I see lower job satisfaction across a variety of dimensions in Table 3. The survey holds the key to interpreting a number of other findings. Many economists believe competitive workplaces are naturally more unpleasant. The literature predicts greater effort, greater sabotage and decreased probability of promotion in competitive settings. In addition, if workers facing competition are more likely to quit, this suggests a distaste for the experiencing competition.

However, an alternative interpretation is possible. Many workers, particularly in a high-achieving environment, may be drawn to the presence of other high-achievers. Despite the competition, workers may find this work satisfying or challenging. They may enjoy working alongside close competition. They may benefit from learning or peer-effects from other high performers. If they indeed benefit from these peer effects, they may find themselves with greater outside options (which would explain the results about quitting).

The subjective satisfaction data shows that do indeed feel a distaste for the workplace competition. Across a variety of measures, workers are less satisfied with their jobs, projects, teammates and managers if they are facing greater promotion competition.

This finding may be surprising to some readers. The level of credentials of the firm's employees are known prior to joining the competition. In some sense, employees may be able to estimate some level of competition. Why would they be surprised or unhappy to face lots of promotion competition and strong opponents for promotions? Overoptimism about one's chances may be one reason. An additional reason comes from anecdotal evidence that many employees are joined the firm in a position beneath their ideal level, and hoped to work their way up through promotion into something more satisfactory. Such workers may aspire to enjoy peer effects from future colleagues, but may be frustrated by competition against peers at their current level.

Table 10 shows effects on specialization, or concentration of effort into a small set of tasks. We see that as competition increases, worker effort becomes concentrated into a smaller set of tasks. In addition to specializing, workers differentiate by choosing orthogonal specializations.

I suggest two interpretations of this behavior. These interpretations are not mutually exclusive; it is likely that both interpretations explain the specialization/differentiation phenomena. One interpretation, inspired by [Ellison and Ellison \(2009\)](#), is that this form of differentiation constitutes "obfuscating." The goal of this behavior is to make comparisons between employees more difficult.

In a tournament setup, this behavior would be rational for players. In contest theory, changes that make comparisons harder could be interpreted as an increase in the "noisiness" of evaluation in the contest. Greater uncertainty in evaluation decreases equilibrium incentives and effort from players and increases player welfare.

In most formal models of tournaments, the "noise" is either an exogenous parameter ([Lazear and Rosen, 1981](#)) or a parameter set by a contest designer ([Morgan et al., 2012](#)). The results of this paper suggest that players in these models – rather than the principle or the environment – may be able to choose their own noise parameter as a function of their specialization decisions in a multi-tasking setup.

A second possible interpretation is that the orthogonal specialization is meant to help the players win the contest through pursuit of comparative advantage. One could imagine that for each dimension of productivity, a) the principle has a "weight" (" β_j ") of value that it places on that type of output, and b) each contestant has a "talent" (" θ_{ij} ") governing his/or her ability to produce that form of output compared to others. To win a close competition, players in this case may "specialize" by putting more effort into comparative advantage in accordance with a relationship between β_j and θ_{ij} .

In this model of comparative advantage, specializing helps the contestant win. This specializa-

tion and differentiation may also benefit the firm by allocating effort into comparative advantages which are positive for the firm's efficiency and productivity. This may be especially good for the firm if there are complementarities between the set of tasks.

The "specialization," "obfuscation" and "comparative advantage" effects of contests are relatively unexplored aspect of the game-theoretic literature on tournaments. These result suggest that these topics are important components of contests in a real-world setting. Because of the possibility that that differentiation creates gains for both the firm and its workers, it may be one unexpected reason this form of incentives are commonly used.

References

- Acemoglu, Daron and Martin Kaae Jensen**, "Robust comparative statics in large static games," in "Decision and Control (CDC), 2010 49th IEEE Conference on" IEEE 2010, pp. 3133–3139.
- Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt**, "Competition and Innovation: an Inverted-U Relationship," *The Quarterly Journal of Economics*, 2005, 120 (2), 701–728.
- Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis**, "Recent Developments in the Economics of Time Use," *Annu. Rev. Econ.*, 2012, 4 (1), 373–397.
- Amabile, Teresa M**, *Creativity in context: Update to "the social psychology of creativity."*, Westview press, 1996.
- Azoulay, Pierre, Joshua S Graff Zivin, and Gustavo Manso**, "Incentives and creativity: evidence from the academic life sciences," *The RAND Journal of Economics*, 2011, 42 (3), 527–554.
- Baker, George P**, "Incentive contracts and performance measurement," *Journal of Political economy*, 1992, pp. 598–614.
- Balafoutas, Loukas, Florian Lindner, and Matthias Sutter**, "Sabotage in tournaments: evidence from a natural experiment," *Kyklos*, 2012, 65 (4), 425–441.
- Bandiera, Oriana, Iwan Barankay, and Imran Rasul**, "Team incentives: Evidence from a firm level experiment," *Journal of the European Economic Association*, 2013, 11 (5), 1079–1114.
- Barankay, Iwan**, "Rank incentives: Evidence from a randomized workplace experiment," *Discussion papers*, 2012.
- Baye, Michael R and Heidrun C Hoppe**, "The strategic equivalence of rent-seeking, innovation, and patent-race games," *Games and Economic Behavior*, 2003, 44 (2), 217–226.
- Becker, Brian E and Mark A Huselid**, "The incentive effects of tournament compensation systems," *Administrative Science Quarterly*, 1992, 37 (2).
- Benabou, Roland and Jean Tirole**, "Intrinsic and extrinsic motivation," *The Review of Economic Studies*, 2003, 70 (3), 489–520.
- Besley, Timothy and Maitreesh Ghatak**, "Status incentives," *The American Economic Review*, 2008, pp. 206–211.
- Blume, Brian D, Timothy T Baldwin, Robert S Rubin, and William Bommer**, "ALL FORCED RANKING SYSTEMS ARE NOT CREATED EQUAL: A POLICY CAPTURING STUDY," in "Academy of Management Proceedings," Vol. 2006 Academy of Management 2006, pp. H1–H6.

- Bodily, Samuel E and Robert F Bruner**, *Enron, 1986-2001*, Darden School, UVA, 2002.
- Boudreau, Kevin J, Nicola Lacetera, and Karim R Lakhani**, "Incentives and problem uncertainty in innovation contests: An empirical analysis," *Management Science*, 2011, 57 (5), 843–863.
- Brown, Clair and Greg Linden**, "Chips and Change," 2009.
- Brown, Jennifer**, "Quitters never win: The (adverse) incentive effects of competing with superstars," *Journal of Political Economy*, 2011, 119 (5), 982–1013.
- Bryant, Adam**, "In head-hunting, big data may not be such a big deal," *The New York Times*, 2013.
- Carlson, Nicholas**, *Marissa Mayer and the Fight to Save Yahoo!*, Twelve, 2014.
- Carpenter, Jeffrey, Peter Hans Matthews, and John Schirm**, "Tournaments and office politics: Evidence from a real effort experiment," *The American Economic Review*, 2010, 100 (1), 504–517.
- Carrell, Scott E, Bruce I Sacerdote, and James E West**, "From natural variation to optimal policy? The importance of endogenous peer group formation," *Econometrica*, 2013, 81 (3), 855–882.
- Caves, Richard E and Michael E Porter**, "From entry barriers to mobility barriers: Conjectural decisions and contrived deterrence to new competition*," *The Quarterly Journal of Economics*, 1977, pp. 241–261.
- Che, Yeon-Koo**, "Design competition through multidimensional auctions," *The RAND Journal of Economics*, 1993, pp. 668–680.
- Cowgill, Bo and Eric Zitzewitz**, "Incentive Effects of Equity Compensation: Employee Level Evidence from Google," *Dartmouth Department of Economics working paper*, 2009.
- Cringely, Robert**, "Triumph of the Nerds–The Television Program Transcripts," *PBS Online*, 1996.
- Drago, Robert and Gerald T Garvey**, "Incentives for helping on the job: Theory and evidence," *Journal of Labor Economics*, 1998, 16 (1), 1–25.
- Dye, Ronald A**, "The trouble with tournaments," *Economic Inquiry*, 1984, 22 (1), 147–149.
- Ehrenberg, Ronald G and Michael L Bognanno**, "DO TOURNAMENTS HAVE INCENTIVE EFFECTS?," *Journal of Political Economy*, 1990, 98, 1307–1324.
- Eichenwald, Kurt**, *Conspiracy of fools: A true story*, Random House LLC, 2005.
- , "Microsoft's Lost Decade," *Vanity Fair*, 2012.
- Eliazar, Iddo I and Igor M Sokolov**, "Diversity of Poissonian populations," *Physical Review E*, 2010, 81 (1), 011122.

- Ellison, Glenn and Alexander Wolitzky**, "A search cost model of obfuscation," *The RAND Journal of Economics*, 2012, 43 (3), 417–441.
- **and Sara Fisher Ellison**, "Search, obfuscation, and price elasticities on the internet," *Econometrica*, 2009, 77 (2), 427–452.
- Frank, Robert H**, *Choosing the right pond: Human behavior and the quest for status.*, Oxford University Press, 1985.
- Fullerton, Richard L and R Preston McAfee**, "Auctioning Entry into Tournaments," *Journal of Political Economy*, 1999, 107 (3), 573–605.
- Garicano, Luis and Ignacio Palacios-Huerta**, *Sabotage in tournaments: Making the beautiful game a bit less beautiful*, Centre for Economic Policy Research, 2005.
- Gladwell, Malcolm**, "The talent myth," *The New Yorker*, 2002, 22 (2002), 28–33.
- Green, Jerry R and Nancy L Stokey**, "A Comparison of Tournaments and Contracts," *Journal of Political Economy*, 1983, 91 (3), 349–64.
- Gubler, Timothy, Ian Larkin, and Lamar Pierce**, "The dirty laundry of employee award programs: Evidence from the field," *Harvard Business School NOM Unit Working Paper*, 2013, (13-069).
- Gürtler, Marc and Oliver Gürtler**, "The optimality of heterogeneous tournaments," Technical Report, Working Papers, Institut für Finanzwirtschaft, TU Braunschweig 2013.
- Hamermesh, Daniel S, Harley Frazis, and Jay Stewart**, "Data watch: The American time use survey," *Journal of Economic Perspectives*, 2005, pp. 221–232.
- Harbring, Christine and Bernd Irlenbusch**, "Sabotage in tournaments: Evidence from a laboratory experiment," *Management Science*, 2011, 57 (4), 611–627.
- Herfindahl, Orris Clemens**, "Concentration in the steel industry." PhD dissertation, Columbia University. 1950.
- Hirschman, Albert**, "National Power and the Structure of International Trade," 1945.
- Hirschman, Albert O**, "The paternity of an index," *The American Economic Review*, 1964, pp. 761–762.
- Holmstrom, Bengt and Paul Milgrom**, "Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design," *JL Econ. & Org.*, 1991, 7, 24.
- Hotelling, Harold**, "Stability in Competition," *The Economic Journal*, 1929, 39 (153), 41–57.

- Kahn, Lisa B and Fabian Lange**, “Employer Learning, Productivity and the Earnings Distribution: Evidence from Performance Measures,” *Review of Economic Studies* (forthcoming), 2014.
- Kahneman, Daniel and Amos Tversky**, “Choices, values, and frames.,” *American psychologist*, 1984, 39 (4), 341.
- Knoeber, Charles R**, “A real game of chicken: contracts, tournaments, and the production of broilers,” *Journal of Law, Economics, & Organization*, 1989, pp. 271–292.
- **and Walter N Thurman**, “Testing the theory of tournaments: An empirical analysis of broiler production,” *Journal of Labor Economics*, 1994, pp. 155–179.
- Kohn, A**, “Punished by rewards: the trouble with gold stars, incentive plans, A’s, praise, and other bribes,” 1993.
- Kőszegi, Botond**, “Ego utility, overconfidence, and task choice,” *Journal of the European Economic Association*, 2006, 4 (4), 673–707.
- Krasnokutskaya, Elena, Kyungchul Song, and Xun Tang**, “The Role of Quality in Service Markets Organized as Multi-Attribute Auctions,” Technical Report, Citeseer 2013.
- Lazear, Edward P**, “Pay equality and industrial politics,” *Journal of Political Economy*, 1989, pp. 561–580.
- **and Sherwin Rosen**, “Rank-Order Tournaments as Optimum Labor Contracts,” *The Journal of Political Economy*, 1981, 89 (5), 841–864.
- Lerner, Josh, Parag A Pathak, and Jean Tirole**, “The dynamics of open-source contributors,” *The American Economic Review*, 2006, pp. 114–118.
- Lewis, Michael**, *Liar’s poker: Rising through the wreckage on Wall Street*, WW Norton & Company, 1989.
- Lewis, Randall A and Justin M Rao**, “On the near impossibility of measuring advertising effectiveness,” Technical Report, Working paper 2012.
- Macan, Therese**, “The employment interview: A review of current studies and directions for future research,” *Human Resource Management Review*, 2009, 19 (3), 203–218.
- MacDonald, Glenn and Leslie M Marx**, “Adverse specialization,” *Journal of Political Economy*, 2001, 109 (4), 864–899.
- Maslow, Abraham Harold**, “A theory of human motivation.,” *Psychological review*, 1943, 50 (4), 370.

- McClelland, David C, John W Atkinson, Russell A Clark, and Edgar L Lowell**, "The achievement motive.," 1953.
- McCullers, John C**, "Issues in learning and motivation," *The hidden costs of reward*, 1978, pp. 5–18.
- McDonald, Paul, Matt Mohebbi, and Brett Slatkin**, "Comparing google consumer surveys to existing probability and non-probability based internet surveys," *Google Whitepaper*, Retrieved from http://www.google.com/insights/consumersurveys/static/consumer_surveys_whitepaper.pdf, 2012.
- McGraw, Kenneth O**, "The detrimental effects of reward on performance: A literature review and a prediction model," *The hidden costs of reward*, 1978, pp. 33–60.
- Michaels, Ed, Helen Handfield-Jones, and Beth Axelrod**, *The war for talent*, Harvard Business Press, 2001.
- Milgrom, Paul and John Roberts**, "An economic approach to influence activities in organizations," *American Journal of sociology*, 1988, pp. S154–S179.
- Milgrom, Paul R**, "Employment contracts, influence activities, and efficient organization design," *The Journal of Political Economy*, 1988, pp. 42–60.
- Moldovanu, Benny, Aner Sela, and Xianwen Shi**, "Contests for status," *Journal of Political Economy*, 2007, 115 (2), 338–363.
- Morgan, John, Dana Sisak, and Felix Vardy**, "On the merits of meritocracy," Technical Report, Tinbergen Institute Discussion Paper 2012.
- Prendergast, Canice**, "The provision of incentives in firms," *Journal of economic literature*, 1999, pp. 7–63.
- Radner, Roy**, "Hierarchy: The economics of managing," *Journal of economic literature*, 1992, pp. 1382–1415.
- Rob, Rafael and Peter Zemsky**, *Cooperation, corporate culture and incentive intensity*, INSEAD, 1997.
- Sacerdote, Bruce**, "Peer effects in education: How might they work, how big are they and how much do we know thus far?," *Handbook of the Economics of Education*, 2011, 3, 249–277.
- Schmidt, E. and J. Rosenberg**, *How Google Works*, Grand Central Publishing, 2014.
- Sheremeta, Roman M**, "Behavioral Dimensions of Contests," Available at SSRN 2476020, 2014.
- Siegel, Ron**, "All-Pay Contests," *Econometrica*, 2009, 77 (1), 71–92.
- Silver, Nate**, "Which polls fared best (and worst) in the 2012 presidential race," *The New York Times*, 2012, 10.

- Simpson, Edward H**, "Measurement of diversity.," *Nature*, 1949.
- Smith, Adam**, "The Wealth of Nations, London: W," *Strahan and T. Cadell*, 1776.
- Stigler, George J**, "A theory of oligopoly," *The Journal of Political Economy*, 1964, pp. 44–61.
- Swisher, Kara**, "'Because Marissa Said So' – Yahoos Bristle at Mayer's QPR Ranking System and 'Silent Layoffs'," *AllThingsD*, 2013.
- Thomas, C William**, "The rise and fall of Enron," *JOURNAL OF ACCOUNTANCY-NEW YORK-*, 2002, 193 (4), 41–52.
- Tirole, Jean**, *The theory of industrial organization*, MIT press, 1988.
- Welch, Jack and John A Byrne**, "Straight from the Gut," *New York*, 2001.
- Yoganarasimhan, Hema**, "Estimation of beauty contest auctions," *Available at SSRN 2250472*, 2013.

Tables and Figures

Table 1: Most wage increases come from promotions

Panel A: Google Consumer Survey, CPS weighted	
<i>Source of Most Recent Real Wage Increase (n=15,540)</i>	
Leaving your employer for a new job	24.1%
Stayed at firm; market-wide increase	26.1%
Asking your employer to match another offer	8.2%
Performing well compared to peers at job	41.6%
<i>"At your job or workplace, are promotion slots limited?" (n=16,377)</i>	
Limited number of promotion slots, even if all workers perform well.	77.4%
Unlimited number of promotion slots. All can be promoted who qualify.	22.5%
Panel B: Firms using tournaments for promotions	
Adobe, AIG, Amazon, American Express, Cisco Systems, Conoco, Dow Chemical, Enron, Expedia, Facebook, Ford, General Electric, GlaxoSmithKline, Goldman Sachs, Goodyear Tire, Google, Hewlett-Packard, IBM, Intel, LendingTree, Lucent, Microsoft, Motorola, Sun Microsystems Valve and Yahoo.	

Notes: **Google Consumer Survey** questions were asked by through a survey created by the author of 10,000 respondents each. The survey was conducted in August 2014. Additional details of the author's survey are discussed in Appendix A. Google published a description and comparative analysis of their methodology in [McDonald et al. \(2012\)](#). To this author's knowledge, the only comparative analysis of GCS' accuracy came from election statistician Nate Silver. Silver's 2012 post-election analysis of polls ranked Google Consumer Surveys the second most accurate poll in the sample of 21 used in his forecasts. [Silver \(2012\)](#) concluded, "Perhaps it wont be long before Google, not Gallup, is the most trusted name in polling."

Table 2: Decisions to Promote

Panel A: Non-score predictors of promotion

	(1) Promoted	(2) Promoted	(3) Promoted
Basic Controls	Yes	Yes	Yes
Worker FEs	No	Yes	Yes
Tenure Controls	No	No	Yes
R^2	0.0704	0.214	0.344
Observation	532272	532272	532272

Panel B: Score-based predictors of promotion

	(1) Promoted	(2) Promoted	(3) Promoted	(4) Promoted
Score	0.0532*** (0.00122)		0.0455*** (0.00136)	0.0508*** (0.00152)
Lag 1 Score		0.0418*** (0.00121)	0.0154*** (0.00129)	0.00619*** (0.00124)
Basic Controls	No	No	No	Yes
Worker FEs	No	No	No	Yes
Tenure Controls	No	No	No	Yes
R^2	0.0193	0.0123	0.0201	0.367
Observations	532272	532272	532272	532272

Panel C: Rank, Score and optimal threshold predictors of promotion

	(1) Promoted	(2) Promoted	(3) Promoted	(4) Promoted
Score	0.0557*** (0.00145)		0.0418*** (0.00466)	0.0103** (0.00482)
Percentile Score		0.181*** (0.00454)	0.0482*** (0.0146)	0.111*** (0.0146)
In 87th Percentile				0.0683*** (0.00549)
Controls	All	All	All	All
R^2	0.366	0.366	0.366	0.367
Observations	532272	532272	532272	532272

Panel D: Local comparisons predict promotion

	(1) Promoted	(2) Promoted	(3) Promoted	(4) Promoted
Score (Global)	0.0557*** (0.00145)		0.0248*** (0.00231)	0.0633*** (0.00156)
Score (Local)		0.0615*** (0.00154)	0.0386*** (0.00257)	
Diff of Local & Global Score				0.0384*** (0.00256)
Controls	All	All	All	
R^2	0.366	0.367	0.367	0.367
Observations	532272	532272	532272	532272

Notes: This table presents regressions of promotions (represented as one or zero) as a function of the level of absolute and relative productivity, measured through subjective performance scores. The unit of analysis is the employee-quarter. All regressions include controls for team size, ..., as well as fixed effects for quarter, job type, job level and a twelve-degree polynomial in the worker's tenure at the firm and tenure in his or her current job. This table presents regressions of ... Dependent variable is ... Unit of observation is: All regressions control for... Standard errors are clustered at the ... level.

Table 3: Promotion Competition and Satisfaction

Job Satisfaction Survey (n~5000)	
Satisfaction with: Company overall.	-0.155**
Satisfaction with: Your manager.	-0.098*
Satisfaction with: Your projects.	-0.174**
Satisfaction with: Your workload.	-0.211***
Satisfaction with: Ability to manage/balance work and personal life.	-0.117**
“There is a climate of trust within company.”	-0.226***
“The people in my work group cooperate to get the job done.”	-0.141***
“I understand how my performance is evaluated.”	-0.341*
“I think my performance on the job is fairly evaluated.”	-0.153**

Notes: This table presents results of instrumental variable regressions on a cross sectional measure of job satisfaction and survey responses. For interpretation, I have used normalized independent and dependent variables. The unit of observation in these regressions is a worker approximately halfway through the sample. The sample size is rounded to the nearest hundred for confidentiality reasons. Standard errors are clustered at the business unit containing the contest. A full discussion of these specifications is included in Section 5.

The instrumented variable “Proximity of Competition” is based on subjective performance scores of each employee’s contest peers in the previous quarter. This measure is described in depth in Section 4.1. The instrument utilizes date-of-hire variation and is described in Section 5.3.

All regressions control for worker, quarter, business unit, and basic job-type and job-level fixed effects. In addition, all regressions control for the focal worker’s tenure at the firm, tenure at his current position performance score in the previous quarter.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Observable Characteristics are Uncorrelated with the Instrument

	(1) Instrument	(2) Instrument	(3) Instrument
Normalized Interview Score	-0.0863 (0.105)	-0.0868 (0.104)	-0.0867 (0.105)
Log(Starting Salary)		0.000398 (0.000729)	0.000290 (0.000752)
Job Level (1-9)			-0.00211 (0.00277)
N	532314	532314	532314

Notes: This table presents regressions of my instrument (described in Section 2) on observable characteristics at the time of hire. Standard errors are clustered at the business unit level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Which Possible Assignments are Realized for New Workers?

Panel A: All Possible Assignments

	(1)	(2)	(3)	(4)	(5)	(6)
Quarter & Team FEs	Yes	Yes	Yes	Yes	Yes	Yes
Team x Quarter FEs		Yes	Yes	Yes	Yes	Yes
Team x Job Type FEs			Yes	Yes	Yes	Yes
Job Type x Quarter FEs				Yes	Yes	Yes
Team x Even Day FEs					Yes	Yes
Team x Quarter x Even Day FEs						Yes
F-test of new FEs=0	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p \sim 1$	$p < 0.001$	$p < 0.001$
R^2	0.0333	0.0643	0.103	0.103	0.103	0.108
Observations	8834760	8834760	8834760	8834760	8834760	8834760
Clusters	41	41	41	41	41	41

Panel B: Removing Team x Quarters with No Hires

	(1)	(2)	(3)	(4)	(5)	(6)
Quarter & Team FEs	Yes	Yes	Yes	Yes	Yes	Yes
Team x Quarter FEs		Yes	Yes	Yes	Yes	Yes
Team x Job Type FEs			Yes	Yes	Yes	Yes
Job Type x Quarter FEs				Yes	Yes	Yes
Team x Even Day FEs					Yes	Yes
Team x Quarter x Even Day FEs						Yes
F-test of new FEs=0	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
R^2	0.0419	0.0591	0.119	0.119	0.119	0.123
Observations	2705099	2705099	2705099	2705099	2705099	2705099
Clusters	41	41	41	41	41	41

Notes: This table presents regressions using a dataset of all possible initial business unit assignments for each employee. Each employee is assigned at most one initial assignment, which is the dependent variable (1=assigned, 0=not). The independent variables are interactions between employee's characteristics upon entry (the date of hire and his type of position) and each team.

The table shows that employees of certain job types are more likely to be assigned to certain teams; this is because of some amount of functional separation within the firm's business units. It also shows that certain professional roles were more popular with certain teams at certain times.

Importantly, the table also shows in the latter columns that arriving on an even or odd day predicts teams assignment. This is because, as described in Section 3, a common way of assigning new employees to units at the firm was based on date-of-hire. In this method, the firm assigned employees in batches on certain days. Workers were given wide latitude to select the timing of arrival, and the timing was generally affected by landlord, spousal, vacation and relocation-related preferences.

Standard errors are clustered at the quarter-of-hire level.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Effects on Effort and Productivity

	(1) Hours	(2) Hours	(3) Output	(4) Output
Competition	0.742*** (0.125)	0.758*** (0.133)	0.171* (0.0930)	0.187** (0.0892)
Controls	No	Yes	No	Yes
Worker FEs	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes
Unit FEs	Yes	Yes	Yes	Yes
Tenure Controls	Yes	Yes	Yes	Yes
R^2	0.619	0.619	0.385	0.385
Observations	532272	532272	532272	532272
Clusters	418	418	418	418

Notes: This table presents results of instrumental variable regressions of effort- and productivity- related out comes in a panel data setting. For interpretation, I have used normalized independent and dependent variables. The unit of observation in these regressions is a worker \times quarter. Standard errors are clustered at the business unit containing the contest. A full discussion of these specifications is included in Section 5.

“Output” refers to the sum of all activity measures. “Hours” refers to the number of hours with productive activity during the period; I use this as a measure of effort. A related variable, “Efficiency” (output per hour) is studied in Table 7 below. The dependent variables “Output” and “Hours” are described in greater detail in Section 4.2.1.

The instrumented variable “Proximity of Competition” is based on subjective performance scores of each employee’s contest peers in the previous quarter. This measure is described in depth in Section 4.1. The instrument utilizes date-of-hire variation and is described in Section 5.3. The F -statistic in the first stage of is 31.

All regressions control for worker, quarter, business unit, and basic job-type and job-level fixed effects. In addition, all regressions control for the focal worker’s tenure at the firm, tenure at his current position performance score in the previous quarter.

The additional “Controls” above refer to controls for higher and lower granularity controls for job type and level, as well as controls for business unit size and composition. These are included and excluded as robustness checks of different plausible specifications.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Effects on Efficiency

	(1) Efficiency	(2) Efficiency	(3) Rollbacks	(4) Rollbacks	(5) % Rollbacks	(6) % Rollbacks
Proximity to Competition	0.511*** (0.0710)	0.525*** (0.0762)	0.00204 (0.00641)	0.00111 (0.00604)	-0.0241 (0.0174)	-0.0236 (0.0176)
Controls	No	Yes	No	Yes	No	Yes
Worker FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Unit FEs	Yes	Yes	Yes	Yes	Yes	Yes
Tenure Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.376	0.376	0.123	0.123	0.0863	0.0863
Observations	532272	532272	532272	532272	532272	532272
Clusters	418	418	418	418	418	418

Notes: This table presents results of instrumental variable regressions of effort- and productivity- related out comes in a panel data setting. For interpretation, I have used normalized independent and dependent variables. The unit of observation in these regressions is a worker \times quarter. Standard errors are clustered at the business unit containing the contest. A full discussion of these specifications is included in Section 5.

“Efficiency” refers to the ratio of output and hours. Similar results for these variables are in Table 6. “Rollbacks” is a measure of engineering quality; a “rollback” is when code is later withdrawn. I include both total lines of code rolled back, as well as percentage of lines of code rolled back. Additional discussion of my measures of efficiency and quality are in 4.2.2.

The instrumented variable “Proximity of Competition” is based on subjective performance scores of each employee’s contest peers in the previous quarter. This measure is described in depth in Section 4.1. The instrument utilizes date-of-hire variation and is described in Section 5.3. The F -statistic in the first stage of is 31.

All regressions control for worker, quarter, business unit, and basic job-type and job-level fixed effects. In addition, all regressions control for the focal worker’s tenure at the firm, tenure at his current position performance score in the previous quarter.

The additional “Controls” above refer to controls for higher and lower granularity controls for job type and level, as well as controls for business unit size and composition. These are included and excluded as robustness checks of different plausible specifications.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Effects on Cooperation

	(1) Peer Bonuses	(2) Peer Bonuses	(3) Doc Edits	(4) Doc Edits
Competition	-0.745*** (0.149)	-0.741*** (0.147)	-0.389*** (0.149)	-0.392*** (0.151)
Controls	No	Yes	No	Yes
Worker FEs	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes
Unit FEs	Yes	Yes	Yes	Yes
Tenure Controls	Yes	Yes	Yes	Yes
R^2	0.227	0.227	0.471	0.471
Observations	532272	532272	532272	532272
Clusters	418	418	418	418

Notes: This table presents results of instrumental variable regressions of cooperation-related outcomes in a panel data setting. For interpretation, I have used normalized independent and dependent variables. The unit of observation in these regressions is a worker \times quarter. Standard errors are clustered at the business unit containing the contest. A full discussion of these specifications is included in Section 5.

“Peer bonuses” refer to roughly \$200 bonuses that employees can give each other publicly to highlight exceptional work by peers. “Edits” refers to edits to internal documentation pages that others within a team; I use this as a measure of hoarding knowledge or sharing it. The dependent variables “Peer Bonuses” and “Edits” are described in greater detail in Section 4.2.3.

The instrumented variable “Proximity of Competition” is based on subjective performance scores of each employee’s contest peers in the previous quarter. This measure is described in depth in Section 4.1. The instrument utilizes date-of-hire variation and is described in Section 5.3. The F -statistic in the first stage of is 31.

All regressions control for worker, quarter, business unit, and basic job-type and job-level fixed effects. In addition, all regressions control for the focal worker’s tenure at the firm, tenure at his current position performance score in the previous quarter.

The additional “Controls” above refer to controls for higher and lower granularity controls for job type and level, as well as controls for business unit size and composition. These are included and excluded as robustness checks of different plausible specifications.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: Effects on Innovation

	(1) Patents	(2) Patents	(3) Ideas	(4) Ideas	(5) Rating	(6) Rating
Proximity to Competition	-0.188 (0.152)	-0.190 (0.154)	0.0351 (0.0219)	0.0265 (0.0220)	0.0795 (0.0659)	0.0481 (0.0568)
Controls	No	Yes	No	Yes	No	Yes
Worker FEs	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Unit FEs	Yes	Yes	Yes	Yes	Yes	Yes
Tenure Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.162	0.162	0.0817	0.0818	0.260	0.262
Observations	532272	532272	532272	532272	527240	527240
Clusters	418	418	418	418	418	418

Notes: This table presents results of instrumental variable regressions of effort- and productivity- related out comes in a panel data setting. For interpretation, I have used normalized independent and dependent variables. The unit of observation in these regressions is a worker \times quarter. Standard errors are clustered at the business unit containing the contest. A full discussion of these specifications is included in Section 5.

“Patents” refer to patent applications rewarded to the focal worker. “Ideas” refers to the number of ideas an employee submitted to an internal system for proposing new ideas. “Rating” refers to the average score assigned to the ideas submitted by the focal worker by peer reviewers. Additional discussion of these measures can be found in Section 4.2.4.

The instrumented variable “Proximity of Competition” is based on subjective performance scores of each employee’s contest peers in the previous quarter. This measure is described in depth in Section 4.1. The instrument utilizes date-of-hire variation and is described in Section 5.3. The F -statistic in the first stage of is 31.

All regressions control for worker, quarter, business unit, and basic job-type and job-level fixed effects. In addition, all regressions control for the focal worker’s tenure at the firm, tenure at his current position performance score in the previous quarter.

The additional “Controls” above refer to controls for higher and lower granularity controls for job type and level, as well as controls for business unit size and composition. These are included and excluded as robustness checks of different plausible specifications.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: Effects on Specialization

	(1) Specialization	(2) Specialization
Competition	1.178*** (0.310)	1.105*** (0.268)
Controls	No	Yes
Worker FEs	Yes	Yes
Quarter FEs	Yes	Yes
Unit FEs	Yes	Yes
Tenure Controls	Yes	Yes
R^2	0.587	0.597
Observations	532272	532272
Clusters	418	418

Notes: This table presents results of instrumental variable regressions of effort- and productivity- related out comes in a panel data setting. For interpretation, I have used normalized independent and dependent variables. The unit of observation in these regressions is a worker \times quarter. Standard errors are clustered at the business unit containing the contest. A full discussion of these specifications is included in Section 5.

Specialization is measured through Herfindahl-Hirschman Index (“HHI”) (Hirschman, 1945) measure of the share of output from various activities. Discussion of the measurement of this variable is in Section 4.2.5.

The instrumented variable “Proximity of Competition” is based on subjective performance scores of each employee’s contest peers in the previous quarter. This measure is described in depth in Section 4.1. The instrument utilizes date-of-hire variation and is described in Section 5.3. The F -statistic in the first stage of is 31.

All regressions control for worker, quarter, business unit, and basic job-type and job-level fixed effects. In addition, all regressions control for the focal worker’s tenure at the firm, tenure at his current position performance score in the previous quarter.

The additional “Controls” above refer to controls for higher and lower granularity controls for job type and level, as well as controls for business unit size and composition. These are included and excluded as robustness checks of different plausible specifications.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Effects on Quitting

	(1)	(2)	(3)
Proximity to Competition	0.105*** (0.0163)	0.113*** (0.0152)	0.113*** (0.0146)
Performance		-0.182*** (0.00337)	-0.169*** (0.00644)
Proximity x Performance			0.0376*** (0.00901)
Controls	Yes	Yes	Yes
Period Controls	Yes	Yes	Yes
Unit FEs	Yes	Yes	Yes
Tenure Controls	Yes	Yes	Yes
Observations	532272	532272	532272
Clusters	418	418	418

Notes: This table presents the results of Cox regressions in panel setting. Each observation is a worker \times quarter. All regressions controls for job type, job level, organizational depth, percentage full time, the department/business unit of the worker and quarterly period fixed effects. Standard errors are clustered at the business unit.

Appendix: For Online Publication Only

A Additional Details about CPS-Weighted Google Consumer Survey

This section contains additional details about the survey reported in Table 1. The two questions were asked independently to separate respondents. Within each survey, the order of multiple-choice answers were randomized. Demographics are inferred by Google through IP address, cookie and browsing history information, and reweighed according to CPS population distribution.

The exact text of Q1 was, “Think about the last time your salary or wages increased. Don’t include raises to keep up with inflation or cost of living. Did the increase come from: a) Leaving your employer for a new job, b) Earning more without other job offers, c) Asking your employer to match another offer, or d) I have never received a raise.”

The exact text of Q2 was, “At your job or workplace, are there a limited number of slots for promotion at a given time? Or, can everyone be promoted simultaneously if they have earned it?” Possible answers were a) “Limited number of promotion slots,” b) “Unlimited number of promotion slots,” c) “Not applicable (unemployed, work alone, or etc).” Percentages in Table 1 exclude respondents who choosing c).