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Abstract

While there has been a lot of research on finding and developing top performers in the workplace, less attention has been paid to the question of how to manage those workers who are harmful to organizational performance. In extreme cases, in addition to hurting performance, such workers can generate enormous regulatory and legal liabilities for the firm. We explore a large novel dataset of over 50,000 workers across 11 different firms to document a variety of aspects of workers' characteristics and circumstances that lead them to engage in "toxic" behavior. We also find that avoiding a toxic worker (or converting him to an average worker) enhances performance to a much greater extent than replacing an average worker with a superstar worker.

Keywords: human resource management, misconduct, worker productivity, ethics, superstar

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1 Introduction

There is an abundance of work that explores how to find, develop, and incentivize top performers so as to enhance organizational performance (Lazear and Oyer (2007) and Gibbons and Roberts (2013)). What this work makes clear is that hiring the right people is very important. Finding the positive outliers—the "stars"—can substantially increase performance (e.g., Azoulay et al. (2010), Sauermann and Cohen (2010), and Oettl (2012)). However, there are outliers from the other side of the distribution that are much less studied: those workers who are harmful to an organization's performance (Banerjee et al. (2012) and Pierce and Balasubramanian (2015)). At their most harmless, these workers could simply be a bad fit, leading to premature termination and a costly search for and training of a new worker. However, more damaging to the firm is a worker who engages in behavior that adversely affects fellow workers or other company assets; we label this type of worker "toxic." A toxic worker may engage in sexual harassment, workplace violence, fraud,or some other breach of important company policy or governmental law. In its most dramatic form, such worker misconduct can cost a firm billions of dollars, as evidenced by JP Morgan's "London Whale" incident with Bruno Iksil.[1] At another extreme, such workers can even mortally harm current or past colleagues, as tragically witnessed in the fatal shooting of WDBJ-TV reporters by their former colleague.[2] But even relatively modest levels of toxic behavior can cause major organizational cost, including customer loss, loss of employee morale, increased turnover, and loss of legitimacy among important external stakeholders (Robinson and Bennett (1995), Litzky et al. (2006), Ermongkonchai (2010) and MacLean et al. (2010)).

The causes of worker misconduct are varied. There is consistent evidence that incentives can play a very important role in causing adverse outcomes (e.g., see Oberholzer-Gee and Wulf (2012), Larkin (2014), and Minor (2014)). There is also

[1] See http://www.bloombergview.com/quicktake/the-london-whale. In this case, it was ultimately not Mr. Iksil himself who was charged (he cooperated with authorities), but rather his supervisor and junior trader.

[2] http://www.cbsnews.com/news/virginia-wdbj-station-shooting-alleged-gunman-posted-video-of-shooting-on-social-media/

evidence suggesting that a worker's personal characteristics are important in determining his ethical behavior (e.g., see Ford and Richardson (1994) and Loe et al. (2000)). Lazear and Oyer (2007) suggest that the selection of workers plays a role at least as important, if not more important than incentives in generating outcomes. Thus, one approach to managing toxic workers—and the approach we focus on in this paper—is simply avoiding them. However, in order to do so, we must be able to identify them ahead of time. By exploring the actual conduct and characteristics of many workers that are quasi-randomly placed across and within different organizations, we identify several individual predictors of toxic workers: overconfidence, poor service-orientation, and a vision of themselves as rule followers.

In addition to these predictors, we also find evidence that an employee's work environment contributes to the likelihood of him becoming a toxic worker (e.g., Vardi (2001) , Greve et al. (2010), and Pierce and Snyder (2014)). Our paper complements the work of Pierce and Snyder (2014) who show that in the setting of automobile emissions testing a worker's environment has significant effects on her individual ethical conduct. Moreover, alongside showing that this environmental effect is also present in a broader setting, we are able to compare the importance of an individual's characteristics and identify which individual characteristics matter in determining outcomes, which adds substantially to our explanatory power. Pierce and Snyder's (2014) findings about the impact of workplace environment, while important, explained only the minority of the variation of outcomes.

We also document other features of toxic workers. Specifically, we find that toxic workers produce greater output than the average worker. Thus, as in Gino and Ariely (2012) and Frank and Obloj (2014), we find that there is a potential trade-off when employing an unethical person: they are corrupt, but they excel in work performance. This might explain how a toxic worker can persist in an organization. However, we find that when their productivity is examined more closely, their quality of work is subpar. Thus, they produce at a faster rate, but at lower quality than their average non-toxic peers.

Finally, we estimate the value of finding a "superstar," defined as workers in the top 1% of productivity, versus the value of avoiding a toxic worker. Succeeding in the latter generates returns of nearly two-to-one compared to those generated when firms hire a superstar. This suggests more broadly that "bad" workers may have a stronger effect on the firm than "good" workers. In many other fields and disciplines researchers have found that a negative has a stronger impact than a positive. For example, in the domain of finance, loss aversion recognizes that in terms of magnitude losses have more of an impact than gains (see Tversky & Kahneman (1992)). In the discipline of psychology it is a generally accepted principle that bad experiences have a stronger hold on our psyches than good ones (Baumeister et al. (2001)). Finally, in the field of linguistics, it has been found that humans preferentially attend to negative words over positive or neutral ones (Estes and Adelman (2008)). It is no surprise to us that these findings hold true in the field of human resource management, as well.

Much of the past research on unethical worker conduct has been based on surveys, self-reports, and intention-based outcomes (Weaver and Trevino (1999) and Greenberg (2002)). Bertrand and Mullainathan (2001) suggest that the mixed results of this past work likely stem from the challenge of empirically examining subjective data. For our setting, we define toxic workers as those who are actually terminated for toxic behavior. Thus, this paper complements this important work by linking personal characteristics of workers quasi-randomly placed within organizations with objective conduct outcomes across a very large, novel data set.

An alternative to avoiding toxic workers altogether, is to reform those already in the organization. With resource constraints it may not be feasible for some, if not most, organizations to pursue this second path. However, since we find that a worker's environment is also important in influencing toxic outcomes, there is some hope that through judicious management of a worker's environment, toxicity can be reduced. Nonetheless, further exploring this channel is beyond the scope of the current paper.

The balance of the paper is organized as follows. The next section develops a theoretical understanding of the problem of toxic workers and explores how we can identify their origins. Section Three presents our main empirical results. Section Four provides a discussion, and our final section concludes.

2 Theoretical Considerations: The Person and the Situation

In this section, we consider a simple theoretical setting to illustrate the link between theory and our identification strategy. We begin by assuming a simple world in which all workers are the same and all environments are the same. That is, the person and the situation are always the same. This will serve as a baseline that will then be modified by allowing for different individuals and different situations one at a time. In this setting, all workers can engage in toxic behavior in a given period. Once they engage in such behavior, they are dubbed a toxic worker.[3]

First assume that P represents the probability that a person will engage in some toxic behavior[4] in a given period. In a worker's first period, she has a P chance of engaging in toxic behavior. This means that she has a $1-P$ chance of working in the next period, assuming a toxic worker is removed from the worker pool. Hence, the chance that a worker makes it beyond period t is $(1-P)^t$,[5] which we denote as the survival rate $S(t)$. In contrast, the chance that a worker *does not* make it to period t is $1-(1-P)^t$, which we denote as the failure rate $F(t)$. Recall that the hazard rate, where $f(t)$ is the density of $F(t)$, is then defined as

[3] In the general case, with different individuals and situations, it makes more sense to define toxic workers as those who are more likely to engage in toxic behavior than those who or not. However, here all workers are toxic workers in that sense, so we use the term toxic worker to denote when such a worker actively engages in toxic behavior.

[4] Here, and throughout when we use the term toxic behavior, we are assuming the kind of behavior that is observable (or that its effects are observable).

[5] Note that with this setup it is equivalent to assume that workers have a constant propensity to engage in misconduct and finally do so in a given period with probability P, after which they are removed from the worker pool, and to assume that workers always engage in a constant level of misconduct and are finally caught and removed with probability P. For this study, what we will actually observe is the removal of a worker (i.e., a termination) who has engaged in toxic behavior.

$$
\begin{aligned}
h(t) &:= \frac{f(t)}{S(t)} \\
&= \frac{-\ln(1-P)^t (1-P)^t}{(1-P)^t} \\
&= -\ln(1-P)^t .
\end{aligned}
$$

The hazard rate tells us the chance that a worker will be a toxic worker at time t, given that she has not yet been toxic up until time t. Not only is this an intuitive measure to consider, but there is a long, rich history of estimating hazard rates. In this simple setup of a constant chance of engaging in toxic behavior for all periods, for all people and all situations, the hazard rate would then simple be a linearly increasing function of time, since $-\ln(1-P)^t = -t\ln(1-P)$. Of course, in practice, we do not expect this to be true. In fact, we expect that the hazard rate is likely a very complex function. For example, even if all people and situations were the same, it could take more than one period for a worker to engage in toxic behavior; perhaps it takes more than one period to learn about and take advantage of an opportunity. In this case, P would increase over time. Alternatively, perhaps a person is more likely to engage in toxic behavior during the formative days and months at a new position; as time passes, she becomes better integrated and less likely to be toxic. Many other possibilities abound. Thus, it seems important not to assume some ex-ante relationship between time and the hazard rate. In our setting, we will refrain from making this assumption for our baseline hazard rate by instead specifying an overall hazard rate of engaging in toxicity for a particular person over time as

$$
h(t)\, f(t|X),
$$

where $h(t)$ is allowed to have an arbitrary relationship between the hazard rate and time and can be viewed as the average relationship between time and the hazard rate. In contrast, the function $f(t|X)$ takes on a value greater or less than 1 as a function of (potentially) both the person and situation across time. In this sense, this approach follows the spirit of Trevino (1986) to simultaneously consider both the person and the situation. Specifically, $f(t|X)$ is a function of the person and the situation at time t, which are captured by the matrix X. In its simplest form, we could assume a world with workers that are sometimes toxic at a periodic rate of $h(t)$ and another set of workers who are never toxic. Thus, $f(t|X)$ would simply be an indicator function, taking on the value of 1 or 0, depending on whether the worker is toxic.

For a richer example, assume after 365 days that an average remaining worker has a 5% chance of engaging in toxic behavior on day 366; this means $h(366) = .05$. However, this chance could increase or decrease as a function of the honesty of a particular worker, as well as her job position. The function $f(t|X)$ is then greater or less than 1 depending on the person (e.g., her level of honesty) and the situation (e.g., her particular job position) at a particular point in time. This flexible setup allows us to model a myriad of real-world settings and is the approach we will use in our estimation, as outlined below. However, first we consider some settings of the person and the situation that we can both measure in our study and expect to matter in terms of outcome.

2.1 Factors of the Person and the Situation

In principle, there are some identifiable factors that are likely to predict toxic behavior, especially when studying actual outcomes. Here we discuss those that we can measure in our data. The empirical proxies for these factors are discussed in section 3.1.

It is well established that other-regarding preferences determine the kinds of actions people choose and that people have heterogenous levels of other-regardingness (e.g., see Andreoni and Miller (2002) and Fisman, Kariv and Markovitz (2007)). All things equal, those that are less other-regarding should be more predisposed to toxicity, as they do not fully internalize the cost that their behavior imposes on others. A way to capture one's degree of other-regardingness is to identify how concerned one is about taking care of another's needs. Those that are service-oriented exhibit care for the needs of others. In contrast, those that show little concern for another's interests are less likely to refrain from damaging others and their property. Thus, *ceterus paribus*, those with poor service-orientation should be more likely to engage toxic behavior.

Hypothesis 1: Workers with poor service orientation are more likely to be toxic

Outside of the business ethics literature, there are also some consistent findings that overconfidence contributes to adverse behavior and outcomes. Petit and Bollaert (2011) document a set of important management and finance papers that have established this link. Broadly, there at least two dimensions that might manifest overconfidence. Thus, toxic behavior should be increasing alongside a worker's degree of confidence, holding all else constant.

Hypothesis 2: Overconfident workers are more likely to be toxic

An apparently straightforward factor for measuring the propensity of misconduct is whether or not a worker agrees that rules should always be followed. It would seem that those who always follow rules are likely to follow ethical rules, as well. However, in certain situations, a rule might need to be broken, perhaps to do the "right thing." History is replete with such examples, and it has become a self-evident truth that some rules are meant to be broken. Thus, subjects who admit that sometimes rules should be broken are likely more honest than those who maintain that rules should always be followed. It also seems self-evident that those who are honest are less likely to engage in misconduct, all things equal. Taken together, this suggests that those claiming rules should always be followed are actually more likely to break the rules via toxic conduct.

Hypothesis 3: Workers that claim the rules should never be broken are more likely to be toxic

Possibly the most important factor in determining whether the work environment will increase the likelihood of misconduct is the likelihood of the worker's colleagues to engage in toxic behavior. Pierce and Snyder (2008) find strong evidence that there are ethical-worker peer effects, akin to productivity peer effects. Thus, using Pierce and Snyder's logic, increased exposure to toxicity should lead to more toxicity.

Hypothesis 4: Increased exposure to other toxic workers makes a worker more likely to be toxic

Practically speaking, certain job positions are likely to lead to different levels of toxic behavior. For example, some positions involve more regular contact with other workers, which could increase or decrease the likelihood of toxicity based on the behavior of those other workers. Furthermore, some positions are easier to monitor than others; a highly un-monitored position may be more likely to breed toxicity. There is also evidence that a job position's degree of task diversity can influence misconduct (Derfler-Rozin et al. (2015)). Hence, the type of position a worker has, *ceterus paribus*, should prove an important factor.

Hypothesis 5: A worker's type of job position should affect his likelihood of toxicity

We now turn to our estimation strategy.

2.2 Estimation Strategy

For our empirical analysis, as with our theoretical discussion, we utilize a proportional hazards model (see Cameron and Trivedi (2005)). This allows us to avoid assumptions about the shape of the base hazard rate $h(t)$ over time. We then assume that this base hazard is modified by

$$f(t|X) \equiv e^{\beta_p \mathbf{x}_{p,t} + \beta_s \mathbf{x}_{s,t}},$$

where $\mathbf{x}_{p,t}$ is a vector of personal traits at time t and $\mathbf{x}_{s,t}$ is a vector of situation characteristics at time t. The role of e is simply to ensure that the composite hazard rate $h(t) f(t|X)$ is never negative.[6] In other words, the baseline hazard rate $h(t)$ can be any arbitrary shape over time, but it may be modified by the person and

[6] Precisely, we need the image of $f(t|X)$ to be in the set $\mathbb{R}^+ \cup \{0\}$, since it must be that $h(t) f(t|X) \in [0, +\infty)$.

situation at time t by $f(t|X)$.

This setup then gives us the following partial log-likelihood function to maximize:

$$\log L = \sum_{j=1}^{D} \left[\sum_{i \in D_j} x_i \beta - d_j \log \left\{ \sum_{k \in R_j} e^{x_k \beta} \right\} \right],$$

where i indexes subjects, x_i is a vector of covariates representing the person and the situation, j indexes failure times in chronological order, D_j is the set of d_j failures at time j, and R_j is the set of all subjects that could potentially fail at time j.

In our empirical setting, we have both many types of workers across workgroups and quasi-random matching to workgroups. Company executives explain that the typical worker placement process is a function of periodic work flow and other forces, which are not predictable. We will show in our robustness section that first placements are approximately random. In addition, we will show that our main effects persist when adding workgroup fixed effects over the first placement. However, since these robustness tests yield similar results to analysis using the full dataset with all placements, we will begin our analysis with the whole, and then turn to individual parts for our robustness tests.

Since we have a very large sample and find that our results are consistent when focusing on quasi-random placement, we also abstract away from separating the notion of engaging in toxic behavior and being terminated for toxic behavior. For variety, we will use multiple phrases such as "a worker engages in toxic behavior," "he is a toxic worker," and "she is terminated for toxic behavior" interchangeably. However, strictly speaking, these phrases all mean that the worker is ultimately terminated for toxic behavior.

3 Empirical Analysis

3.1 Data

The data were obtained from a company that builds and deploys job-testing software to large employers. In fact, many of these companies are business-process outsourcers

(BPOs) that themselves provide a variety of business services (e.g., customer care, outbound sales, etc.) to their clients. The employees included in the dataset are all engaged in frontline service positions and paid on an hourly basis. From these organizations, we were able to obtain and combine three separate datasets on the basis of employee IDs:

1) Job-testing data: The vendor supplying the data has developed a proprietary job test that assesses applicant fit for the position for which applying. We were able to obtain the employee scores on this job test (i.e., Green, Yellow, Red) as well as the responses to select questions that appeared on the test.

2) Attrition data: All of the companies with which the vendor engages provide an attrition feed that indicates (among other things) the employee's hire date, termination date (as applicable), reason for termination, their location, job title, and the supervisors to whom they reported while employed by the firm.

3) Performance data: For a subset of employees included in our analysis, we were able to obtain daily performance data that represent productivity by measuring the average amount of time an employee required to handle a transaction and customer satisfaction scores indicating how well she served the customer.

Common employee IDs across all three of these datasets allowed us to merge them together in order to look at relationships between assessment responses and an employee's likelihood of engaging in toxic behavior. In total, the dataset covers 11 firms, 184 sub-firms (end clients of BPOs), 2,882 workgroups, each reporting to a particular supervisor, and 58,542 workers. Table 1 provides a summary of our main variables of interest.

From the assessment data, we were able to obtain several different measures of worker quality and predicted performance.

Each employment assessment is designed by an industrial-organizational psychologist and attempts to measure an employee's knowledge, skills, and abilities. We were able to obtain a portion of this proprietary analysis. In particular, we have a prediction of how service-oriented a given worker might be. This assessment is based on some questions that could be construed as measuring the degree of "other-regardingness" of a worker. Here is a sample set of choices presented to applicants:

1. I like to ask about other people's well-being

   OR

2. I let the past stay in the past

Choosing statement 1 would give subjects a greater service-oriented score. The variable Low Service Orientation is a dummy variable with value 1 if the assessment predicts the subject will be poor at service; otherwise, the variable has a value of 0.

Also included in the overall assessment were questions intended to gauge an applicant's technical ability. Applicants were asked early in the assessment to self-assess their computer proficiency and they were then tested on several key computer skills. We compared their self-assessment to their actual computer proficiency in order to develop a measure of applicant self-confidence. The variable Skills Confidence Level is constructed by extracting the residual from a regression of actual skills (i.e., measured skills) on promised skills (i.e., given by the worker). That is, this variable is a measure of how much the actual skills exceed or fall short of the promised skills.[7]

We acknowledge that this variable could also be a measure of honesty. Though, 11% of workers actually *under-promise* their skills level, which would make this an unlikely measure of dishonesty in such an incentivized setting. Furthermore, if it becomes apparent after hire that a worker has lower-than-promised skills, there is a real chance that she will be terminated. Finally, we still find similar results if we simply drop the 34% of workers who overpromise performance. Thus, it seems this variable is more a measure of confidence in one's own abilities than a measure of honesty.

Several questions on the assessment asked applicants about their propensity to follow rules. We were also able to obtain these questions and the applicant responses in order to understand whether there was a relationship between the response option an applicant endorsed and her likelihood to engage in toxic behavior. In particular, applicants were asked to choose one option from each of the two sets of statements:

[7] We also calculate Skills Confidence as simply the difference between stated and actual skills without using regression analysis, and the results are similar. In absolute terms, we find that roughly 11% of workers promise lower skill than they deliver, 55% deliver as they promise, and 34% overpromise.

1. I believe that rules are made to be followed. OR

2. Sometimes it's necessary to break the rules to accomplish something

and

1. I like to see new places and experience new things. OR

2. I complete activities according to the rules.

For each of the rule-following variables constructed, a 1 means that the worker chose the statement that rules should be followed (i.e., the first statement in the first set and the second statement for second set). Thus, receiving a 1 on these dummy variables means that a subject is stating that he feels rules should be followed.

The Density of Toxic Workers is a ratio that measures the degree of a worker's exposure to other toxic workers. That is, it is the ratio of other workers on a worker's team who are ultimately terminated for being toxic, as described below, divided by the current number of workers on the worker's team. Thus, this measure changes over time.

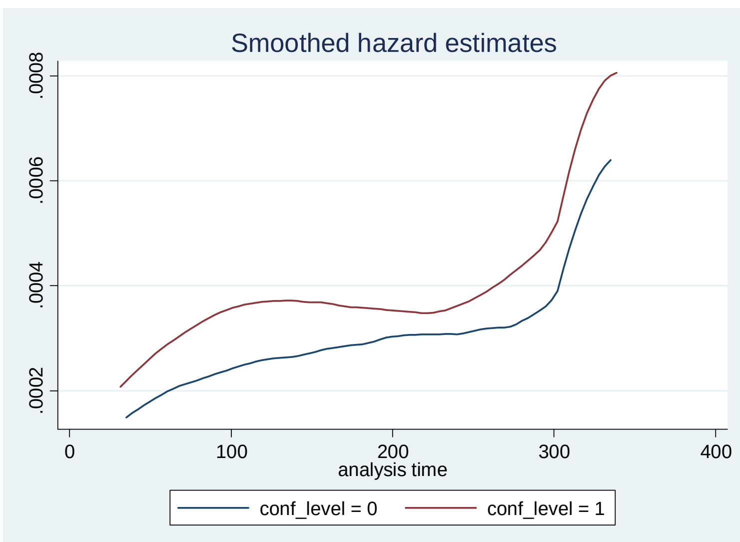
For a subset of the dataset, we also have quantitative performance data. We have a measure of worker output speed and we have the length of time needed to complete one unit of output. The variable Performance Quantity Time FE is an individual worker fixed effect calculated while regressing the time-per-unit of a worker on a cubic function of time-on-the-job experience and controls for job position and the sub-firm where the worker is employed, while achieving a given performance result. We generally have multiple observations of a worker's performance over time; we refer to each observation of performance measurement as a performance result. In addition, we have a measure of worker output quality. This variable Performance Quality is obtained analogously to the variable Performance Quantity Time FE.

Finally, our dependent variable is an indicator variable based on whether the worker is terminated for toxic behavior. Toxic behavior is defined as involuntary termination due to an egregious violation of company policy. Examples include sexual harassment, workplace violence, falsifying documents, fraud, and general workplace misconduct. The mean of this variable is approximately 1% across all observations. However, in terms of per worker, the mean is 4.5% of all observations. In other words, roughly 1 in 20 workers is ultimately terminated as a toxic worker.

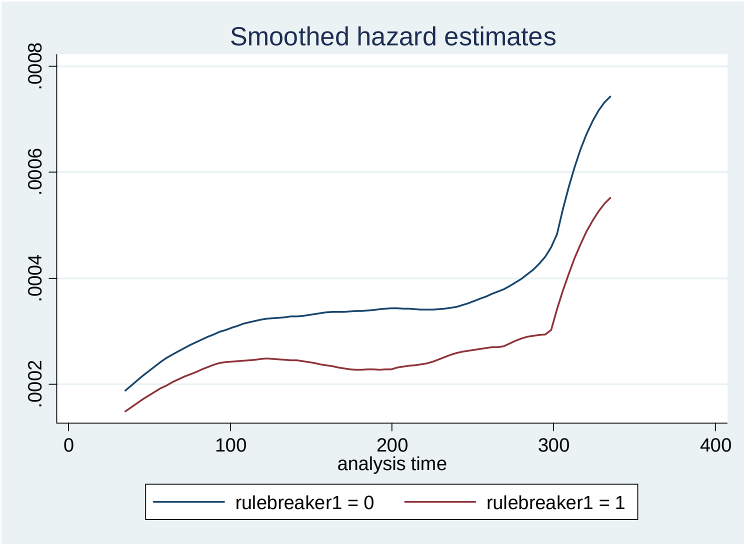
3.2 Hazard Functions

In this section, we show some graphical examples of the hazard rate as a function of time. In the next section, we will conduct a full analysis with controls. To provide sufficient observations we report the hazards for the first 365 days, as over 90% of a worker's tenure is under one year.

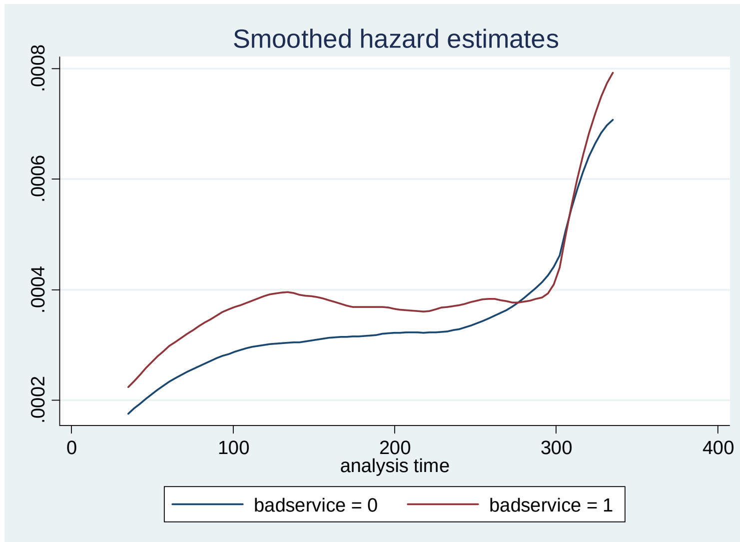
The first chart compares the difference in hazard rates of workers with an above-average (i.e., conf_level=1) and a below-average (i.e., conf_level=0) Skills Confidence Level. Those who appear overconfident by overreporting their skill level before they start the job are more likely to be terminated for toxic behavior across all time.



Next we estimate the hazard rates of workers that state rules should never be broken (i.e., rulebreaker1=0) and those that suggest sometimes breaking rules is necessary (i.e., rulebreaker1=1). Interestingly, those that claim the rules should never be broken are more likely to be terminated for breaking the rules as a toxic worker across, at all times.



Finally, we compare the hazard rates of those with poor service orientation versus others. As can be seen, having a poor service orientation makes one more likely to be terminated for toxicity. If a worker that has a poor service orientation is not terminated for toxicity in the first year, thereafter their chance of termination for toxicity is more similar to other workers. It could be that those workers with poor service orientation that also engage in toxicity are largely eliminated from the worker pool by this time.



Although these charts are suggestive, these estimated hazard rates need to be interpreted with care; they do not include potentially important controls. Further, we need to consider different factors simultaneously to determine if they are different predictors of toxic workers or if they are a measure of the same underlying force. For this analysis, we turn to our proportional-hazards regression model.

3.3 Regression Analysis

3.3.1 Baseline

Table 2 reports the results of our baseline regression model.[8] For these regressions, we have a large enough sample to stratify by each sub-firm. This means that each sub-firm is allowed to have a unique baseline hazard function $h(t)$. That is, it is as if we estimate each regression sub-firm by sub-firm. As can be seen, greater reported Skills Confidence results in a greater chance of being terminated for being a toxic worker. In particular, a one standard deviation in Skills Confidence results in an

[8]For all of our hazard models, we test the proportionality assumption (i.e., that the composite hazard rate is of the form $h(t)\, f(t)$) on the basis of the Schoenfeld residuals after fitting a given model (see Grambsch & Therneau (1994)). In all cases, our model is consistent.

approximate 15%[9] increase in the hazard. That is, conditional on a worker not yet having been terminated as a toxic worker, a one standard deviation increase in Skills Confidence means that there is some 15% greater hazard of termination due to toxic behavior. Similarly, those that have a poor service-orientation, have more than a 22% increased hazard of toxic termination. If a worker reports that she believes rules are made to be followed (as opposed to stating that it is sometimes necessary to break the rules to accomplish something), she has about 25% greater hazard of being terminated for actually breaking the rules. Finally, a worker that has a one standard deviation increase in exposure to toxic workers himself experiences a 46% increased hazard in being terminated for engaging in toxic behavior.

If we categorize the first four columns as measures of the person and the last two columns (including particular job type) as measures of the situation, we can state what fraction of a toxic worker's origin is attributable to the person versus the situation. In particular, using McFadden's pseudo R^2, we calculate that approximately 70% of the explanatory power of the model beyond a model with only an intercept comes from the person, and the balance (i.e., 30%) from the situation. If each variable in each column mattered equally, we would expect the person to explain 2/3 of outcome (i.e., 4 out of 6). In the next section, when we only analyze a worker's first placement, we find from using McFadden's pseudo R^2 that person explains almost 88% of the outcome. In short, at least in our setting, there is important explanatory power in simply knowing the person, though the situation certainly matters too, and it seems to matter more over time.

Since we can only measure those cases of toxicity that are discovered and eliminated through termination, we could be only partially measuring outcomes. For the kinds of toxic behavior that we're studying (e.g., extreme levels such as sexual harassment and workplace violence) it seems likely that when such behavior is exhibited, discovery and termination will usually occur. However, in principle, it could be that cleverer people are better at somehow hiding their behaviors. To explore this

[9] Recall that to convert estimates into a hazard ratio, simply raise e to the coefficient value. For example, a coefficient value of .5 results in $e^{.5} \simeq 1.65$. This means a one unit change in the regressor amounts to a 65% increase in the hazard ratio. Alternatively, a one standard deviation increase, when such standard deviation is .225, results in a roughly 14.6% increase in the hazard ratio.

possibility, we were able to obtain the results of two cognitive tests that applicants take. These tests represents two questions, each quantitatively based with an objective correct answer. Table 3 reports the results of adding these two measures to our previous analysis. In doing so, we found that our previous estimates are very similar and that the cognitive test results do not explain the likelihood of toxic terminations. In fact, one test has a positive coefficient point estimate and the other test has a negative one, though neither is significant.

Ideally, we would like to conduct our analysis after randomly allocating all workers to workgroups and then observing their experiences and performance over time.

Doing so would average out possible confounds for which it is difficult to control. For example, perhaps a particular workgroup is better (or worse) at detecting and eliminating toxic workers. However, based on discussions with company executives, conditional on a given sub-firm, a worker's first placement tends to be essentially random. Exactly where an employee is initially placed depends on a variety of factors outside the control of the worker and the workgroup in which she is placed. For example, the work flow of a particular operation, demand and supply shocks, and exactly when a worker turns up looking for a job are all factors determining to which group a new hire will be assigned. Further, a workgroup supervisor does not generally choose her group's new worker, so the supervisor does not observe the new worker's predicted job fit and other individual characteristic covariates that we use in our analysis. However, a worker's second placement may not be essentially random. Thus, for a robustness test, we now redo our above analysis, but only for a worker's first placement.

3.3.2 First Placement Only

Table 4 reports an analysis based only on an employee's first placement. As can be seen, the results are broadly similar to the case in which all worker placements are included. Upon closer inspection, we see that the magnitude of the coefficient of the toxic worker density is about 20% smaller. One possible explanation for this is that the exposure to toxic workers has a cumulative effect: the same exposure over a greater period of time has a greater adverse effect on a worker.

In principle, we can test statistically whether a placement is different from random. One common method includes comparing covariates across treatments, where treatments normally total two. However, in our setting, a "treatment" is the initial placement in each workgroup, which amounts to $2,882$ treatments, making a comparison cumbersome. Further, one can only consider relationships pair-by-pair. However, another common method that also allows the covariates to be interdependent is using a logit or probit model to predict treatment. Of course, this method only works when there are two different treatments; again, we have $2,882$ treatments. However, we can analyze a multinomial equivalent where each outcome is considered an unordered outcome of being placed in a given workgroup. We need sufficient observations in order to estimate how each covariate contributes to the likelihood of being placed in a particular workgroup. In the end, we can estimate how covariates predict 985 workgroup placements.

The following table reports the results of these regressions.

	Low Service Orientation	Skills Confidence	Rules: Sometimes Break	Rules: Prefer Adventure
Number of Workgroups Significant at 5%	47	113	50	101
Fraction of Estimated Workgroups (985)	4.77%	11.47%	5.08%	10.25%
Fraction of All Workgroups (2,882)	1.63%	3.92%	1.73%	3.50%

We find that in 47 of the 985 cases Bad Job fit predicts in which workgroup a worker is placed in, which represents almost 5% of workgroups. Skills Confidence is significant over 11% of the time, whereas Rules covariates are significant at 5% and 10% of the time, respectively. If all placements were generated at random, we would expect each covariate to be significant at the 5% level, 5% of the time, on average. When we consider the full dataset we are using to estimate effects in our main analysis, covariates are only significant less than 3% of the time, on average. The reason we cannot estimate covariate effects on the entire dataset of workgroups is that generally there are too few observations for a particular workgroup, which also means we do no expect such workgroups to create statistical aberrations on their own.

We ran an additional robustness test to explicitly control for a employee's workgroup during her first placement. In particular, we run a linear panel model with workgroup fixed effects for a worker's first placement.[10] Here, we collapse the exposure to toxic workers as an average exposure over the placement, whereas before this was the current-period exposure. Results are reported in Table 5. The findings with this linear model are very similar in terms of significance and magnitude when compared with our hazard models, with the exception of the effect of Toxic exposure . In terms of magnitudes, a worker that is predicted to have Low Service Orientation has an additional .9% chance of becoming a terminated toxic worker, which is an increase of 20% from the baseline toxic worker rate of 4.5%. A one standard deviation in Skills Confidence results in a roughly 11% chance of becoming a terminated toxic worker. Those who state that rules should never be broken are 20% more likely to be terminated for toxic behavior. A one standard deviation increase in exposure to other toxic workers induces a roughly 98% increased chance of a worker becoming a toxic worker. Finally, In short, these effects are consistent with those found with our previous models.

3.3.3 Toxic Worker Performance

For a subset of the data, we have performance data on the workers. For this group, as discussed in section 3.1, we have a measure of each employee's time to produce one unit of quantity and a measure of their quality of work. We then use this data to calculate a worker-specific fixed effect of each of these measures, which we refer to as Performance Quantity Time FE and Performance Quality FE, respectively.

Looking simply at mean FE values, we find that the average Performance Quantity Time FE is less for those ultimately fired for toxicity than those that are not toxic (t-test with unequal variance yields a p-value= .0376). That is, toxic workers are more productive than those that are not ultimately terminated for toxicity. When

[10] Note that we do not control for position type in these specifications. A particular workgroup typically consists of the same set of position types, and thus the variance matrix naturally becomes unusable when we do attempt to control for position type simultaneously with workgroup.

we consider Performance Quality FE, we find that toxic workers have lesser quality than non-toxic workers; however, results do not quite reach conventional levels of statistical significance (p-value= .1233). Of course these are simply means and we should consider analysis with controls. In particular, we need to relate the productivity of workers and whether or not that worker is terminated for toxic behavior while controlling for the previous factors that are important for identifying toxicity.

Table 6 reports the results of introducing these additional measures to our original analysis reported in Table 2. The other variables of interest previously studied are qualitatively the same as in table 2, although the levels of significance are diminished for this considerably smaller sample size.

Similar to our findings of comparing the means, those who are terminated for engaging in toxic behavior are more productive than non-toxic employees; equivalently, those who are slower (i.e., large values of Performance Quantity Time FE) are *less* likely to be toxic. In terms of magnitude, a one standard deviation in time per unit of production results in a 56% reduction in the hazard of becoming a toxic worker. However, those workers with poorer *quality* performance are more likely to be toxic. Here, a one standard deviation increase in the quality of production results in a 27% decrease in the hazard. With controls, this relationship is not significant at conventional levels.

It might seem that toxic workers are simply those that trade work quality for speed and those workers that produce higher quality must also be slower workers. However, this is not the case. Clearly, there is a natural tradeoff between speed and quality of work. Yet, there are almost 50% more workers that produce high quality work quickly (32.4% of workers) than those that produce low quality work quickly (23% of workers). Thus, although toxic workers are quicker than the average worker, they are not necessarily more productive in a quality-adjusted sense. In the long run, these kinds of workers are not likely to improve overall organizational performance.

Finding Superstars vs. Losing Toxic Workers With performance data we can also compare the strategy of finding a "superstar" worker versus avoiding a toxic one. As discussed in the introduction, many firms, as well as the extant literature are focused on finding and keeping the next star performer, whereas much less attention is devoted to avoiding toxic workers. Given a firm with limited resources, which strategy is more fruitful? Although we certainly cannot answer this question for all possible settings, we can asses this trade-off for our setting.

To generate a straightforward comparison of the value of each of these focuses, we quantify the value of a star performer by identifying the cost savings from her increased output level. That is, without such a star performer, a firm would have to hire additional workers to achieve the same output they enjoy when they have a superstar. In the table below, the column "Hire a Superstar" reports the cost saving based on the top 1%, 5%, 10%, and 25% performers. We calculate the percent in increased performance for each of these performance levels and multiply it by the average worker salary, based on company records. This is an upper bound of the cost-savings from hiring a Superstar since increased performance is often accompanied by increased wages.

For comparison, we report in the "Avoid a Toxic Worker" column the induced turnover cost of a toxic worker, based on company figures. Induced turnover cost captures the expense of replacing additional workers lost in response to the presence of a toxic worker on a team. The total estimated cost is $12,489 and does not include other potential costs, such as litigation, regulatory penalty, and reduced employee morale. Also not included are the secondary costs of turnover that come from a new worker's learning curve: a time of lower productivity precedes a return to higher productivity. Thus, this estimate is likely a lower bound on the average cost of a toxic worker, at least for this empirical setting.

	Cost-savings	
Superstar Rank	Hire a Superstar	Avoid a Toxic Worker
top 25%	$ 1,951	$ 12,489
top 10%	$ 3,251	$ 12,489
top 5%	$ 3,875	$ 12,489
top 1%	$ 5,303	$ 12,489

In comparing the two costs, even if a firm could replace an average worker with one who performs in the top 1%, it would still be better off by replacing a toxic worker with an average worker by more than two-to-one. That is, avoiding a toxic worker (or converting them to an average worker) provides more benefit than finding and retaining a superstar. Assuming that it is no more costly to avoid a toxic worker (or replace them with an average worker) than it is to find, hire, and retain a superstar, it is also more profitable to do the former over the latter. Of course, this differential between the superstar and toxic worker might not be as drastic in other settings. Nonetheless, finding a top 1% worker can be both difficult and costly. Further, sometimes "stars" that hiring managers discover via another firm are not able to transport their same elevated level of productivity to their next employer (Groysberg (2012)). Finally, as some high-stakes finance workers recently showed us leading up to the Great Recession, high-flying lines of work can generate both superstars and toxic workers with enormous impacts.

4 Discussion

Based on our analysis, we have a variety of takeaways for managers. From our study, it seems clear that toxic workers originate both as a function of preexisting characteristics and the environment in which they work. In particular, we found consistent evidence that those who seem overconfident in their abilities, who are poorly service-oriented, and who claim rules should be followed, are more likely to become toxic workers and break the rules. One strategy for hiring managers is to screen potential workers for these traits to reduce the chance of hiring toxic workers. Of course, there are more dimensions to a good (and bad) hire beyond whether or not candidates have a higher propensity to become toxic. Worker productivity is also important. Interestingly, we found that toxic workers are apparently more productive, at least in terms of the quantity of output. This could also explain how toxic workers are able to remain in an organization for as long as they do. For example, an investment bank with a rogue trader who is making the firm millions in profits might be tempted to look the other way when the trader is found to be overstepping the rules. Pierce and Snyder (2013) find unethical workers enjoy longer tenures. However, we also found evidence that the quality of production for these workers is lower. This means that eventually, the value of the higher productivity will be diminished, perhaps drastically, as the consequences of lower-quality work are manifested.

This performance finding suggests that toxic workers are similar to what Jack Welch described as "Type 4" workers—those that deliver on the numbers but do not have the right values. Welch claimed that while difficult to do, it was critical to remove such workers: "People are removed for having the wrong values...we don't even talk about the numbers" (Bartlett and Wozny (2005)). Thus, we find evidence that such a policy—one that removes the "big shots" and "tyrants" seems to be one that would lead to more productive organizations in general.[11] Similarly, Delong and Vijayaraghavan (2003) argue that the top performers are not always the best workers to pursue over even the average worker, as the former can also create organizational issues, including reckless behavior.

Although we do find certain preexisting traits that predict toxic workers, this does not mean that those traits were always present in the worker. Though it is beyond the scope of this paper, it would be interesting to learn to what extent work-life experiences breed the preexisting traits that we have found to lead to toxic workers. It would be very valuable to discover what firms can currently do to limit the chances of converting a "normal" worker to a future toxic worker.

In this vein, we did find that a worker's environment also substantially influenced her propensity to become a toxic worker. We documented that holding a particular type of position, as well as exposure to other toxic workers negatively influenced the likelihood of one becoming toxic. Hence, this suggests that managing toxic workers is not simply a matter of screening them out of the firm, but also minding the work environment.

[11] We thank Tarun Khanna for this Jack Welch example.

5 Conclusion

In the end, a good or bad hiring decision is multidimensional (Lazear & Oyer (2007) and Hermalin (2013)). We have identified several personality and situational factors that lead to a worker engaging in objective toxic behavior. Knowledge of these factors can be used to better manage for toxic workers. We have also discovered some important effects of toxic workers. However, there are surely additional traits that could be used to identify toxic workers. Similarly, it would be helpful to know which other environmental factors nudge an otherwise normal worker towards becoming a toxic worker and possibly creating the preexisting workplace conditions that lead to toxic behavior. Future research can shed light on these questions. This latter focus seems particularly important, because to the extent that we can reduce a worker's propensity to become toxic, we are helping not only the firm, but the worker himself, those around him, and the potential firms where that employee may work in the future. Since we found some evidence that a toxic worker can have more impact on performance than a "superstar," it may be that spending more time limiting negative impacts on an organization might improve everyone's outcome to a greater extent than only focusing on increasing positive impacts. We have taken a first step in exploring this notion and hope that we witness future progress in this area.

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Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Low Service Orientation	248370	0.15	0.35	0.00	1.00
Skills Confidence Level	248370	-0.01	0.23	-0.24	0.92
Rules: Sometimes Break Them	248370	0.14	0.34	0.00	1.00
Rules: Prefer Adventure	248370	0.44	0.50	0.00	1.00
Density of Toxic Workers	248370	0.04	0.04	0.00	0.80
Performance Quantity Time FE	62618	-32.77	213.11	-462.94	1488.31
Performance Quality FE	20089	-0.05	0.13	-0.91	0.23
Terminated for Toxic Behavior	248370	0.01	0.10	0	1

Table 2: Terminations as a Function of Worker Type and Environment

(All Placements)

Outcome: Terminated Toxic Worker

Worker and Environment	(1)	(2)	(3)	(4)	(5)	(6)
Low Service Orientation	0.2808***	0.2090***	0.2077***	0.2047***	0.2030***	0.2023***
	(5.30)	(3.81)	(3.78)	(3.71)	(3.69)	(3.68)
Skills Confidence Level		0.5215***	0.5206***	0.5177***	0.5033***	0.5034***
		(6.42)	(6.41)	(6.36)	(6.18)	(6.17)
Rules: Sometimes Break Them			-0.2373***	-0.2284***	-0.2247***	-0.2272***
			(-3.75)	(-3.55)	(-3.49)	(-3.53)
Rules: Prefer Adventure				-0.0274	-0.0193	-0.0184
				(-0.67)	(-0.47)	(-0.45)
Density of Toxic Workers					2.5581***	2.5182***
					(11.74)	(11.49)
Position Controls	No	No	No	No	No	Yes
Log Likelihood	-18446.4880	-18427.3077	-18419.9216	-18419.6990	-18372.5281	-18368.2087
N	246599	246599	246599	246599	246599	246599

Cox proportional hazard model used for estimation

Non parametric hazard functions estimated at the sub-firm level

Z scores reported in parentheses based on standard errors clustered at the worker level

* p<0.10, ** p<0.05, *** p<.01

Table 3: Cognitive Scores and Terminations

(All Placements)

Outcome: Terminated Toxic Worker

Worker and Environment	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive Test I Correct	0.0051	0.0164	0.0200	0.0201	0.0304	0.0258
	(0.10)	(0.32)	(0.39)	(0.39)	(0.59)	(0.50)
Cognitive Test II Correct	-0.1092*	-0.0777	-0.0708	-0.0693	-0.0581	-0.0599
	(-1.76)	(-1.25)	(-1.14)	(-1.11)	(-0.93)	(-0.96)
Low Service Orientation	0.2730***	0.2051***	0.2043***	0.2015***	0.2004***	0.1996***
	(5.12)	(3.73)	(3.71)	(3.65)	(3.64)	(3.63)
Skills Confidence Level		0.5126***	0.5129***	0.5104***	0.4982***	0.4978***
		(6.27)	(6.28)	(6.23)	(6.08)	(6.06)
Rules: Sometimes Break Them			-0.2355***	-0.2273***	-0.2241***	-0.2264***
			(-3.72)	(-3.53)	(-3.48)	(-3.52)
Rules: Prefer Adventure				-0.0257	-0.0180	-0.0169
				(-0.63)	(-0.44)	(-0.41)
Density of Toxic Workers					2.5560***	2.5151***
					(11.71)	(11.45)
Position Controls	No	No	No	No	No	Yes
Log Likelihood	-18444.8609	-18426.5004	-18419.2375	-18419.0419	-18371.9870	-18367.6758
N	246599	246599	246599	246599	246599	246599

Cox proportional hazard model used for estimation

Non parametric hazard functions estimated at the sub-firm level

Z scores reported in parentheses based on standard errors clustered at the worker level

* p<0.10, ** p<0.05, *** p<.01

Table 4: Terminations as a Function of Worker Type and Environment

(First Placements Only)

Outcome: Terminated Toxic Worker

Worker and Environment	(1)	(2)	(3)	(4)	(5)	(6)
Low Service Orientation	0.3279***	0.2617***	0.2608***	0.2638***	0.2595***	0.2597***
	(5.66)	(4.35)	(4.33)	(4.37)	(4.30)	(4.30)
Skills Confidence Level		0.4574***	0.4573***	0.4603***	0.4545***	0.4513***
		(4.96)	(4.96)	(4.98)	(4.91)	(4.86)
Rules: Sometimes Break Them			-0.2058***	-0.2146***	-0.2111***	-0.2097***
			(-2.95)	(-3.02)	(-2.96)	(-2.95)
Rules: Prefer Adventure				0.0272	0.0311	0.0300
				(0.59)	(0.67)	(0.65)
Density of Toxic Workers					2.1341***	2.1409***
					(7.47)	(7.48)
Position Controls	No	No	No	No	No	Yes
Log Likelihood	-13661.0461	-13649.4261	-13644.9028	-13644.7302	-13627.5793	-13626.9476
N	190178	190178	190178	190178	190178	190178

Cox proportional hazard model used for estimation

Non parametric hazard functions estimated at the sub-firm level

Z scores reported in parentheses based on standard errors clustered at the worker level

* p<0.10, ** p<0.05, *** p<.01

Table 5: Linear Model of Terminations with Workgroup Fixed Effects

(First Placements Only)

Outcome: Terminated Toxic Worker

Worker and Environment	(1)	(2)	(3)	(4)	(5)
Low Service Orientation	0.0128***	0.0093***	0.0093***	0.0097***	0.0091***
	(4.04)	(2.86)	(2.87)	(2.96)	(2.82)
Skills Confidence Level		0.0243***	0.0243***	0.0246***	0.0208***
		(5.07)	(5.06)	(5.11)	(4.39)
Rules: Sometimes Break Them			-0.0074***	-0.0083***	-0.0076***
			(-2.74)	(-3.01)	(-2.79)
Rules: Prefer Adventure				0.0028	0.0025
				(1.33)	(1.23)
Avg Density of Toxic Workers					1.1078***
					(20.70)
R Squared	0.044	0.044	0.044	0.045	0.070
Adjusted R Squared	0.022	0.023	0.023	0.023	0.049
N	44710	44710	44710	44710	44710

t statistics reported in parentheses based on standard errors clustered at the workgroup level

* p<0.10, ** p<0.05, *** p<.01

Table 6: Terminations with Worker Performance

(All Placements)

Outcome: Terminated Toxic Worker

Worker and Environment	(1)	(2)	(3)
Performance Quantity Time FE	-0.0036***		-0.0039***
	(-6.79)		(-5.33)
Performance Quality FE		-2.1925***	-2.4419***
		(-4.90)	(-5.28)
Low Service Orientation	0.0383	-0.0620	-0.0853
	(0.41)	(-0.41)	(-0.55)
Skills Confidence Level	0.4069***	0.4597**	0.4686**
	(2.93)	(2.50)	(2.54)
Rules: Sometimes Break Them	-0.0215	-0.0226	0.0192
	(-0.20)	(-0.14)	(0.12)
Rules: Prefer Adventure	-0.0823	-0.2627***	-0.2449**
	(-1.17)	(-2.64)	(-2.44)
Density of Toxic Workers	1.5359***	1.7591***	1.5971***
	(5.21)	(5.83)	(5.15)
Position Controls	Yes	Yes	yes
Log Likelihood	-5859.5624	-3233.1108	-3165.6394
N	62419	19983	19751

Cox proportional hazard model used for estimation

Non parmetric hazard functions estimated at the sub-firm level

Z scores reported in parentheses are based

on standard errors clustered at the worker level

* p<0.10, ** p<0.05, *** p<.01