

Integrity, Creativity, and Corporate Culture

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Abstract

We develop a new measure of integrity as it relates to corporate culture—the number of employees who use corporate emails to register for a website that facilitates extramarital affairs. This measure is associated with firm-level unethical behavior: it predicts a greater probability of SEC enforcement actions for accounting misstatements, lower corporate ethics ratings by external analysts and is associated with tax-avoidance. However, consistent with research in psychology, we find that the measure also predicts more innovation. Our results suggest that it is difficult to engineer a perfect corporate culture due to potential trade-offs between creativity, and integrity.

Keywords: Corporate culture, Integrity, Creativity, R&D

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1 Introduction

Managers often assert that having an appropriate culture is critical to a firm’s success. For example, in a recent survey of CEOs and CFOs by Graham, Harvey, Popadak, and Rajgopal (2015), 91% of respondents said that they thought that culture was “Important” or “Very Important”, and 78% think that it is a top 5 value driver for their firm. One particular dimension of culture that has received much attention from regulators, auditors and academics is the degree of integrity in a firm’s culture and its relationship with corporate fraud.¹ Despite the importance of culture to regulators, auditors, and managers, there is relatively little quantitative research that tests whether an unethical culture actually predicts corporate fraud. This is perhaps because culture, by its very nature, is difficult to define and measure. Most research relies on surveys and interview to measure culture, which provide important insights into some facets of culture. However self-reporting biases may be particularly severe for surveys of integrity: for example, employees of firms with questionable ethics are perhaps more likely to lie or embellish their responses to surveys.

In this paper, we move beyond self-reported measures to study a measure of integrity based on individual employee actions: the decision to register for and use AshleyMadison.com (“AM”), a website that facilitates extramarital affairs.² We assign AM users to firms based on the domain name taken from their email IDs, resulting in a sample of approximately 47,000 individuals who used their corporate email ID to register and actively use an AM account over the 2002-2014 period. Our key variable of interest is the number of active users at any point in time in a given firm, where *active* means the user has not only registered, but also exhibited some activity in the account (e.g. purchased credits to send a message).

We hypothesize that AM membership reflects a firm’s emphasis on integrity for two reasons. First, Erhard, Jensen, and Zaffron (2009) argue that “keeping one’s word” is an important component of integrity for individuals and organizations. Using AM reflects a lack of integrity at the

¹For example, in a speech to members of the financial services industry on October 20, 2014, William Dudley, President and Chief Executive of the Federal Reserve Bank of New York says: “*Supervisors simply do not have sufficient “boots on the ground” to ferret out all forms of bad behavior within a giant, global, financial institution. Moreover, regardless what supervisors want to do, a good culture cannot simply be mandated by regulation or imposed by supervision...It is up to you to address this cultural and ethical challenge.*”

²We use anonymized data on individual users and do not conduct any analysis at the user level. Furthermore, we do not disclose in any way the names of corporations with employee email IDs in the database. We have received exemption from Institutional Review Board approval by the universities with which we are associated because of the anonymization process, public availability of the data, and the aggregate nature of the measures that enter our analysis.

level of the individual employee, since the AM website encourages users not to keep their word to a significant other (the website's slogan is *Life is short. Have an affair*). Because a firm is more likely to attract, select, and retain employees who match its culture (Schneider, 1987), we expect that individual employee traits provide information about corporate priorities. Firms that do not emphasize integrity in their cultures are more likely to employ individuals who display a lack of integrity.

Second, the decision to use an official email id for a private purpose suggests that the employee (correctly or incorrectly) believes that their firm does not monitor email usage, or infers that there will be no consequences if they are found out. Thus, the decision to use an official email id may itself provide information on the systems and policies in place at firms. Overall, AM membership reflects both a focus on integrity at an individual employee level and the focus on integrity of systems and policies in place at firms.

We test whether AM membership predicts future corporate fraud. In particular, we test whether firms with greater AM membership are more likely to be subject to SEC enforcement actions due to accounting misstatements. Dechow, Ge, Larson, and Sloan (2011) find that a host of financial variables predict SEC enforcement actions. We find that controlling for all these variables, greater AM membership predicts a greater likelihood of *future* enforcement actions. Moreover, these results are economically significant: A one standard deviation increase in AM membership predicts that the likelihood of fraud is 0.104%, which is more than double the unconditional mean. As far as we know, we are the first paper that shows that corporate culture actually predicts fraud with a measure that is based on the revealed preference of rank and file employees.

Despite its advantages, AM membership is by no means a perfect measure of corporate ethics. One potential concern is that we can only observe the fraction of employees who use their official email id to register for AM. Besides perceptions of systems in place, there could be other reasons to use an official email id that are likely to make AM membership a noisy measure of corporate ethics.³ Another related concern is that the number of AM users that we observe constitutes a small fraction of firm's workforce. Around 50% of firms have zero AM membership and the mean AM membership is 5.4 employees for the firms that have at least one AM member. While the small

³For example employees could be unfamiliar with the perils of electronic communications, may believe that their spouse does not have access to official email id, or may simply be reckless.

fraction of AM membership likely adds noise to the measure, it should also bias against finding results.

We therefore run a battery of tests to ensure that the relation between AM membership and corporate fraud is robust. First, rather than using the number of AM employees which could be noisy, we test whether a simple dummy variable that is one if there is at least one AM account in a firm predicts misstatements. We find that this dummy variables also predicts future misstatements. Another concern is that there may be heterogeneity across industries or geographies in AM usage. All our results survive industry and geography fixed effects. There also may be non-linearities in fraud with respect to firm size. We therefore match firms on size (number of employees) and show in the Internet Appendix, that AM firms are 75% more likely to have accounting misstatements than non-AM firms.

Finally, it is possible that these results may be specific to the choice of accounting misstatements as a measure of fraud. We therefore test whether AM membership predicts an alternative measure of corporate ethics: ratings of firms on ethical issues by external analysts at KLD. We find that a one standard deviation increase in AM membership is associated with a 2.65% increase in analysts perception of significant concerns regarding bribery and corruption. This effect is economically quite large, since the unconditional average is only 4.7% and the average for firms with no membership is 3.39%. We also find that AM firms are more likely to be involved in tax avoidance via use of tax havens, pay lower taxes than similar companies, and are more likely to be rated as having tax-related concerns by KLD analysts.

A natural question is why unethical cultures continue to exist. Why don't all firms put in place internal systems and emphasize norms that encourage integrity? One possibility is that cultures that display more unethical behaviors also have some benefits that allow them to survive in a competitive market. In particular, we hypothesize that there is tradeoff between an ethical, rules-driven, process-oriented culture and a culture that encourages innovation and risk taking. For example in Graham, Harvey, Popadak, and Rajgopal (2015), entrepreneurial cultures are described by participants with words such as "start-up culture," "aggressive," "scrappy," "dynamic," "charming chaos," "innovative," "thinking outside of the box" and "reaching beyond the obvious.", while high integrity cultures described as "compliance driven," "credibility focused," "accuracy of financials". We hypothesize that it is difficult to be both 'innovative' and 'compliance-driven'.

This tradeoff can arise for two reasons. First Gino and Ariely (2012) find creative individuals are also more unethical in a series of experiments. They suggest that this is because both creativity and unethical behavior require patterns of thinking that involve rule-breaking. They argue that creative people are more likely to be dishonest because creative thinkers are able to find creative, but potentially unethical loopholes to solve difficult problems, and they are able to invent creative rationalizations for dishonest behavior.⁴ Second, the trade-off could also arise if creative firms lack extensive controls because their creative employees feel constrained by bureaucracies. Such firms may be subject to ethical or legal violations, even in the absence of a creativity-ethics trade-off at the individual level, because they do not have adequate systems that provide checks and balances.

Consistent with an creativity-ethics tradeoff, we find that AM membership also predicts creativity at the firm level. Higher AM membership predicts a host of innovation measures including R&D intensity and efficiency, successful patent application rates, subsequent patent citations, and patent diversity. For example, a one standard deviation increase in AM membership is associated with an increase in R&D efficiency (Patents/R&D) of 0.02, which is roughly 28% of the unconditional mean. Similarly, a one standard deviation increase in AM membership is associated with an increase in citations by about 20% of the unconditional mean.

The relationship between creativity and ethics can arise because of a selection effect: Firms select employees to fit their existing cultures Schein (1992). By itself, an endogenous matching of employees with firms is interesting because it results in an equilibrium tradeoff between integrity focused and creative cultures, which has not been documented before. However, it is also interesting to investigate whether there is a causal relation between firm culture and innovation beyond the selection channel. To do so, we examine shocks to culture stemming from acquisitions. Although acquisitions are a choice variable determined by a firms senior management, it is unlikely that individual inventors at large firms have much control over M&A activity. We therefore examine the impact of mergers on the innovation of serial inventors from the target firm. According to our hypothesis, an inventor coming from a creative, risk-taking culture that is acquired by a firm with a relatively stricter culture may become subject to greater constraints, adversely affecting creativity (and vice versa). We find evidence that this is indeed the case: the difference between the acquirers

⁴It is important to note that unethical behavior and creativity are by no means perfectly correlated. For example, the authors of this paper would like to believe that we are both ethical and creative (as are our readers).

and the targets AM membership intensity matters for a given inventors post-merger innovation. In particular, post-merger patenting activity, within a given inventor, decreases to a greater extent when targets are acquired by firms with relatively stricter cultures (lower AM membership) when compared to those acquired by firms with relatively more relaxed cultures.

Our results provide two key insights. First, at a minimum, AM membership captures an important source of unobserved heterogeneity across firms, which predicts substantive firm-level outcomes. After controlling for other standard predictors, AM membership has incremental predictive power for future accounting misstatements and external analyst perceptions of unethical behavior. These results are consistent with the hypothesis that firm culture and ethical behavior are closely linked. Second, our results suggest that there is a trade-off between an ethical, rules-driven, process-oriented culture and a culture that encourages innovation and creativity. This trade-off could arise because creative firms need creative employees, and creative employees are more likely to be unethical due to the association between creativity and unethical behavior identified in Gino and Ariely (2012) or because creative employees select into, or are selected by firms with looser internal controls. Note that firms may not make this trade-off consciously. For example, firms that are innovative may currently focus their recruitment only on personalty traits related to creativity; our results show that screening for and encouraging ethical behavior is particularly important for such firms. Overall, our results provide an explanation for why we don't observe all firms gravitate toward one "ideal" corporate culture. Different cultures have differing costs and benefits, and there are no black and white answers to what constitutes a perfect culture; there are only shades of gray.

Our paper contributes to the literature that examines corporate culture. O'Reilly and Chatman (1996) define culture as "a set of norms and values that are widely shared and strongly held throughout the organization," while Deal and Kennedy (1982) define culture more pithily as "the way things get done around here." Kreps (1990) argues that culture is necessary because contracts can be incomplete. If employees can be trusted to act in certain ways when unforeseen events arise, more efficient outcomes can be realized.⁵ The purpose of corporate culture, under this definition is to complement formal control systems and influence behavior such that desired outcomes are realized in situations beyond the reach of formal control systems. AM membership is likely to capture both informal norms and formal systems and processes (at least with regards to the use

⁵See Baldvinsdottir, Hagberg, Johansson, Jonll, and Marton (2011) for a good overview.

of information technology). In practice, both formal systems and informal norms are likely to be driven by the same underlying values, and distinguishing between these alternatives is beyond the scope of this paper.

Our paper is specifically related to research that attempts to quantify corporate culture. Kim, Park, and Wier (2012) use analyst ratings to examine whether socially responsible firms are also responsible along various dimensions of financial reporting. Popadak (2013) measures culture based on a textual analysis of employee reviews of firms from career intelligence websites, and finds that stronger shareholder governance causes firms to focus on observables and neglect intangibles such as collaboration and integrity. Guiso, Sapienza, and Zingales (2015) and Garrett, Hoitash, and Prawitt (2014) measure integrity using surveys that ask employees whether they believe that senior managers in their firms are ethical. We also focus on integrity, but our measure is akin to a revealed preference. Rather than survey employees, we infer the importance of integrity in a firm's culture using the actions of a subset of the firm's employees.

Moreover, our results are related to prior research that examines the effect of CEO personality on firm outcomes (e.g., Jia, Lent, and Zeng (2014), Schrand and Zechman (2012), and Gormley, Matsa, and Milbourn (2013)). In particular, recent work by Mironov (2015), Cline, Walkling, and Yore (2016), and contemporaneous work by Griffin, Kruger, and Maturana (2016) shows that CEOs' personal indiscretions and corrupt behavior are associated with firm level corruption, ethical violations, and class action lawsuits. While we also document a strong association between personal and professional ethics, our analysis is broader in the sense that it includes all employees of a firm and not only upper management. This is consistent with anecdotal evidence that suggests that "rank and file" employees and not top management were responsible for unethical corporate behavior in a number of recent corporate scandals.⁶ Moreover, the choice of CEO is endogenous with respect to firm culture; we find that firms with lax cultures are more likely to choose internal CEOs relative to firms with more ethical cultures, thereby perpetuating their current culture.

Our results also complement those in previous studies that document drawbacks of a lack of

⁶For example, AIG's Joseph Cassano and Drexel Burnham Lambert's Dennis Levine, both employees well below the level of corporate executive, each played a large role in their firm's troubles during the financial crises of 2008 and the late 1980's, respectively. Similarly, it appears that engineers, and not top executives, at Volkswagen installed software intended to mislead emissions testing. While it is likely that Martin Winterkorn (the CEO) played a role in determining the culture, it was the ethics of rank and file employees that led to scandal, and ultimately a large loss in shareholder wealth.

integrity in culture, by showing that there are advantages to lax cultures. These results have a similar flavor to Hirshleifer, Hsu, and Li (2013) and Mironov (2015) who find advantages to overconfident and corrupt CEOs in certain contexts.

2 Data

2.1 The AshleyMadison Data

AshleyMadison.com is a dating website for people who are married or in a committed relationship. The website was created in 2002 and quickly became the world’s largest online social networking community for people who wish to engage in extramarital affairs.⁷ While signing up on AshleyMadison is free, users must purchase credits to send custom messages, initiate chat sessions, send priority messages, or send virtual gifts. By late August 2015, information for the majority of AshleyMadison accounts was released on BitTorrent. The data quickly became available on a variety of websites and received a great deal of media attention.⁸

Many of the accounts on AshleyMadison were registered using corporate email addresses. Our interest is in linking these email accounts to their respective firms. In particular, we use WebURL from Compustat and LexisNexis corporate affiliations to obtain a list of corporate email domains from the AM database. We merge this list to the Compustat database using ticker symbol and company name. We then hand-check each domain-company link to verify its validity. We exclude certain domains that are likely being used by people who are not employed at the firm to which the domain belongs. For example, we exclude domains such as “yahoo.com,” “facebook.com,” “aol.com,” “google.com,” and “verizon.com”. After applying these filters, our final sample includes 12,687 company domains in the Compustat database from 2002-2014 . Using these domains, we are able to match 46,649 employees to companies who used the corporate domain name with which they created an AshleyMadison account from 3,469 different companies. We do not in any way disclose the names of individuals or corporations that have accounts in our dataset.

For each account we observe the date that the account was created, the age of the user, the

⁷<http://www.prnewswire.com/news-releases/hollywood-courts-toronto-based-ashley-madison-75587257.html> "Hollywood Courts Toronto-based AshleyMadison". www.prnewswire.com. Retrieved 2015-10-24.

⁸For example, on August 19, 2015 the Washington Post published that thousands of accounts were linked to the U.S. military and the U.S. government. *Inside Higher Ed* reported that more than 74,000 accounts at AshleyMadison were from universities and colleges with ‘.edu’ email accounts.

gender of the user, the city (zip-code) in which the account was created, the first date that an email or message was sent, the last date that an email or message was sent, and whether the account user purchased any credits. For the majority of our analysis, we restrict our focus to accounts that exhibited some level of activity (e.g., a custom message was sent, a chat session was initiated, or credits were purchased for the account). This excludes “phantom” accounts that were created by mistake, as a practical joke, or by someone who immediately appears to have had second thoughts about their actions.⁹ Furthermore, since we can only observe the dates for the first and last email, or message, we assume that an account is active in the intermediate time between its inception and the last observed activity. We define the variable $activeaccount_{j,t}$ as a binary variable equal to unity for the years in which an account is active according to our definition, and zero otherwise.

We create our primary variable, $active\ AM\ accounts_{i,t}$, by summing the number of accounts with a corporate domain name that belongs to firm i and that have exhibited some level of activity on or before time t :

$$active\ AM\ accounts_{i,t} = \ln \left(\sum_{\tau=0}^t \sum_{j=1}^N \mathbb{1}[domain(activeaccount_{j,t}) = corpdomain_i] + 1 \right).$$

We use the natural log of the number of active AM accounts as our main variable, and not the ratio of AM accounts to the total number of employees at a firm, because the Compustat item, emp (i.e., the number of employees) is only an approximation.¹⁰ We control for the (log) number of employees and (log) market capitalization in all our specifications. We repeat our analysis using a scaled version of our measure in the Internet Appendix in Tables A.7-8 and find qualitatively similar results.¹¹ As a robustness check, we also use a dummy variable as an alternative dependent variable equal to one if the number of active AM accounts is greater than zero, and zero otherwise.

Table 2, Panel A reports the basic descriptive statistics. The average age of an AM user is 39

⁹In unreported results, we relax this restriction to include possible “phantom” accounts and the results are largely unchanged.

¹⁰The number of employees at a firm is not an audited number and firms strategically misreport employment numbers (e.g., Beatty and Liao, 2012). As a result, there is not a standard way for firms to report this number (e.g., some firms report the average number of employees and some report the number at year-end). In addition, the emp item typically includes part-time, seasonal, and foreign employees. Scaling by a number that includes foreign employees could potentially bias our results, since our AshleyMadison measure is composed of only domestic employees. Finally, there are only a few AshleyMadison accounts per firm, relative to the total number of employees at the firm. Taking the ratio would result in a denominator that is several orders of magnitude larger than the numerator and that exhibits a large degree of measurement error.

¹¹Specifically, we the log of the ratio of Active AM accounts to the number of Employees as measured by Compustat

year old and the ratio of males to females is around two to one.¹² Table 2 reports industry and geographic statistics for our sample. As table 3 documents, Ashley Madison services are used by high-tech industries, while low tech and defense are on the bottom. We choose to control for that via industry fixed effects.

2.2 Other data

For data on corporate social responsibility, we use the MSCI KLD STATS from 2002-2014. KLD data are detailed annual statistics of performance indicators developed by MSCI analysts who provide research for institutional investors. To create these performance indicators, MSCI analysts use government databases, company disclosures, and macroeconomic data to assess company performance with respect to meeting stakeholder needs regarding environmental, social, and governance factors. Mattingly and Berman (2006) and Kim, Park, and Wier (2012) suggest that the KLD data is well suited for studying corporate social responsibility. Note that Kim, Park, and Wier (2012) document a strong association between KLD ratings and financial reporting standards, which is reassuring for our analysis since we use both as proxies for corporate ethics. For the purpose of our study, we focus on the particular indicators we consider to be closely related to integrity, which is the dimension of corporate culture we intend to study.¹³ The KLD indicators are broken down into *strength* and *weakness* categories.

Our first variable, *Bribery and Fraud* is a binary variable equal to unity if a firm has experienced severe controversies related to bribery, tax evasion, insider trading, and accounting irregularities in a given year, and zero otherwise. Similarly, *Tax Disputes* indicates whether a firm has had major tax disputes within a given year. The variable *Product Quality* assesses how companies manage their risk of facing major product recalls or losing customer trust through major product quality concerns. Companies that score higher are those that proactively manage product quality by achieving certification to widely acceptable standards, undertaking extensive product testing, and building processes to track raw materials or components. The variable *Human Rights* measures the severity of controversies related to a history of involvement in human rights-related legal cases;

¹²In unreported results, used only males or females, as well as males/females user ratio for given firm. The results are qualitatively similar to those reported in the paper.

¹³While we subjectively chose the five indicators we believe to best summarize the nature of our results, a much more extensive analysis of the KLD measures is provided in the appendix.

widespread or egregious complicity in killings, physical abuse, or violation of other rights; resistance to improved practices; and criticism by NGOs or other third-party observers. Firms that are guilty of worse human rights violations have negative scores. Lastly, *profit sharing* indicates whether a company has a cash profit-sharing program through which they have recently made distributions to a significant proportion of their workforce. Note that the first two variables (*Bribery and Fraud* and *Tax Disputes*) are binary, and the other KLD variables are the sum of binary sub-components and hence can take on values other than 0 or 1. All variables are defined in detail in Table 1.

Data on misstatements from 2002-2014 come from the AAER data set discussed in Dechow, Ge, Larson, and Sloan (2011). This dataset provides detailed information regarding SEC investigations of public corporations for financial misstatements and has been commonly used in accounting research to study misreporting. Schrand and Zechman (2012) use these data to show that overconfident CEOs are more prone to misstatements due to optimism, and then eventually become compelled to misstate earnings intentionally. Feng, Ge, Luo, and Shevlin (2011) study the AAER database to provide evidence that CFO's are involved in material accounting misstatements because of pressure from CEOs. In a closely related study to ours, Garrett, Hoitash, and Prawitt (2014) use the AAER database to show that trust in top management, measured at various employee ranks, is a significant predictor of financial reporting quality.

Our tax havens data are from Dyreng and Lindsey (2009), who download every 10-K on SEC's Edgar database between 1994 and 2014 and search every 10-K filing (Exhibit 21) for country names. Countries are identified as tax havens if they are defined as such by three of the four following sources: (1) Organization for Economic Cooperation and Development (OECD), (2) the U.S. Stop Tax Havens Abuse Act, (3) The International Monetary Fund (IMF), and (4) the Tax Research Organization.

We use patent data from the National Bureau of Economic Research (NBER) patent data project, the Harvard Patent Database (Li, Lai, DAmour, Doolin, Sun, Torvik, Yu, and Fleming, 2014), and the patent data from Kogan, Papanikolaou, Seru, and Stoffman (2014) (henceforth KPSS). Hall, Jaffe, and Trajtenberg (2001) (henceforth HJT) provide a detailed description of the NBER data, which include over 3 million patents and 16 million patent citations. The patent data cover the period 1976-2006. We extend this sample, using the Harvard Patent Database, which has updated the patent application information through 2010 and KPSS data, which has added

information on patent citations updated through 2012. The Harvard Patent Database also includes detailed information on individual inventors, which we use for our inventor analysis in section 3.3.

It is well-documented that patenting (citation) propensities exhibit tremendous heterogeneity across patent technology classes and through time.¹⁴ In this paper we follow related finance literature and employ a reduced-form approach to adjust for patent class propensities, as suggested by Hall, Jaffe, and Trajtenberg (2001), Seru (2014) and Lerner and Seru (2015). The procedure involves sorting patents into 6 major technological classes and 36 subcategories. Each patent is then scaled by the average number of patents filed by other firms in each technology class subcategory and application year. We use the 36-category adjustment because it contains more information. Citations are adjusted by dividing by the average number of citations in each class - grant year. These adjusted patents (citations) are then aggregated at the firm-year level, creating a weighted sum of each firm's patents.

From the patent data, we create measures of innovative activity that are consistent with recent finance literature on innovation [e.g., Kogan, Papanikolaou, Seru, and Stoffman (2014)] and develop a few of our own. First, we define *Patents* as the raw number of truncation and propensity-adjusted patents at the firm-level. This measure captures the level of intermediate inputs (i.e. the number of patent applications) for firm-level innovation. While we control for patenting propensities across time and technology classes, we can still make use of the diversity of a firm's patent portfolio. We define a firm's patent portfolio to be more diverse if it is less concentrated on technology subcategories. Specifically, we define the measure of patent diversity as,

$$Pdiv_{i,t} = \left[1 - \sum_{c=1}^{36} \left(\frac{\text{npatents in tech class } c \text{ in year } t}{\text{total patents applied for in year } t} \right)^2 \right]$$

A firm with zero diversity, meaning 100% of its patents are concentrated in one technology class, will have a *Pdiv* measure of zero. A firm that patents equally (as a percent of total patents) in all technology classes will have a measure of $0.9722 = 1 - 1/36$. The average firm in our sample has a patent diversity measure = 0.099 with a sample standard deviation of 0.23. A large fraction of firms ($\approx 60\%$) patent in only one technology class, implying they have a measure of zero. We create analogous measures for citation (*Cdiv*) and adjusted citation (*ACdiv*) diversity.

¹⁴Lerner and Seru (2015) discuss the problems with truncation effects and patenting propensities in detail.

In addition to patent counts and diversity, we create measures of innovative intensity and success. For instance, $Patents/R\&D$ represents the number of patents applied for in a given year scaled by lagged research and development expenses, through which we intend to capture a measure of R&D success, as well as control for inputs in generating patentable technology. For each firm-year we also calculate the number of patents that are in the top 10% of the distribution of citations within a grant-year and patent category. These measures have been used as proxies for innovation quality or influence (e.g., Balsmeier et. al., 2014). To compare these measures with a measure of innovation that is less dependent on patent variables, we include $R\&D/sales$ (research and development expense scaled by contemporaneous sales) as a measure of innovation input intensity. When possible, we create analogous measures at the inventor-level for our quasi-experimental analysis in section 4.4. Specifically, we calculate the number of patents, the number of citations, the number of patents in the top 10%, and the number of citations per patent for each inventor-year.

Firm accounting and financial information come from Compustat from 2001-2014. We also use stock price and return data from CRSP to calculate volatility measures and portfolio returns. A full description of all variable definitions is provided in the Table 1 of the Internet Appendix.

3 AM membership and corporate outcomes

3.1 Corporate Ethics

In this section, we examine whether greater AshleyMadison membership among the employees in a firm is related to unethical behavior by the firm, after controlling for other determinants of unethical behavior that are standard in the literature (see Dechow, Ge, Larson, and Sloan (2011)). As before we consider SEC enforcement actions for accounting misstatements and KLD ratings as our measures of unethical behavior.

First, we follow related work by Schrand and Zechman (2012), Garrett, Hoitash, and Prawitt (2014), and Jia, Lent, and Zeng (2014) and use SEC enforcement actions due to misstatements to study financial reporting quality. The auditing standards board (AU-C Section 240, Consideration of Fraud in a Financial Statement Audit) states that there are three determinants of fraud: *opportunity*, *pressure* (or incentives), and *attitude* (this is related to character and lack of ethical values). We proxy for opportunity with measures of governance such as insider ownership and the GIM

index. We proxy for pressure with firm profitability (i.e., ROA) and industry competition (i.e., Herfindahl index), and we proxy for ethical culture using AM membership. We use predictive probit regression specifications, in which misstatements are predicted by lagged values of independent variables.

We follow Dechow, Ge, Larson, and Sloan (2011) and run three models Model 1 (Specifications 1 and 2) includes AM-variables and financial statement variables. Model 2 (Specifications 3 and 4) adds nonfinancial-statement and off-balance-sheet variables, and Model 3 (Specifications 5 and 6) incorporates market-based measures. As Dechow et al (2011), we use logit model. We augmented their models by adding industry and year fixed effects. We report the results in Table 4, Panel A.

AM membership strongly predicts the probability of accounting misstatements, after controlling for other potential determinants studied by Dechow, Ge, Larson, and Sloan (2011). The unconditional probability of misstatements in our sample is 0.67%. Increasing Active AM Accounts by one standard deviation results in increasing of misstatement probability by 0.36 to 0.53 %, or by 54 to 79% of unconditional mean. The effect is even more drastic in specifications using *Dummy(AM_{it})*. There companies with AM accounts present have 0.84 to 1.06% higher probability of misstatements. That is equivalent to 126 to 159% of unconditional mean. Other variables are in general agreement with Dechow et al (2011).

To look at the issue further, we created matched sample for AM firms. We matched firms in the same year, and same Fama-French 48 industry, with the closest Number of Employees. The latter match must be within 10%. ¹⁵ For each AM firm, we tried to find the firm without AM accounts. It is important to note that the criterias employed were quite tough and resulted in relatively high losses of observations. In firms with positive number of AM accounts, the probability of misstatements is 1.19%, and in matching sample without AM accounts, the same probability is 0.68%. The difference (0.51%, or 75% of probability of misstatements in companies without AM Membership) is significant at 10% level.

We then turn to KLD ratings in Table 4. We first examine five categories that are related to corporate ethics: Bribery and Fraud, Tax Disputes, Human Rights, Product Quality, and Sharing.

¹⁵We also tried matching on market capitalization and value of assets. Those matches agree with the ones reported. It is important to note that our matching procedure is skewed towards smaller firms, as large firms of hundred thousands employees might have one account by chance. Thus, we might not find appropriate match for larger firms. However, the robustness of our results under the added rigidity of the matching procedure increases our confidence that we have uncovered a strong economic association between corporate ethics and creativity.

First variable of interest is closely related to accounting misstatements, however, it is larger in scope. While Misstatements is dealing with observed and recording wrongdoing, Bribery and Fraud (reported in Specifications 1 and 2) is based on expert opinion (as well as observed misdeeds). Greater AM Membership is associated with instances of ethics 56

We observe similar results for Tax Disputes (Specifications 3 and 4). One standard deviation of Active AM Accounts (Presence of AM Accounts) is associated with 72% (79%) higher instances of tax disputes with respect to unconditional mean of 2.1%. Larger (as measured both by number of employees and market capitalization) companies and companies with larger idiosyncratic volatility are more likely to be involved in such disputes.

The results for human rights violations are similar, although weaker (Specifications 5 and 6). Companies with higher AM Membership are more likely to be involved with regimes that violate human rights (have conflicts with indigenous people, or have labor disputes) and less likely to have proactive policies that prevent such involvement¹⁶. The effect is about 39

Specifications 7 and 8 reports the results for product quality concerns. Higher AM Membership is related to more concerns (coded as negative number), and less strengths (coded as positive number). The economic effect for Active AM Accounts ($Dummy(AM_i0)$) is 63% (67%) of unconditional mean¹⁷.

So far, we showed that AM membership is associated with number of negative corporate behavioral traits. Specifications 9 and 10 are looking at Employee Sharing (variable that indicates whether a company has a cash profit-sharing program through which they have recently made distributions to a significant proportion of their workforce). The results show that AM firms are more likely to have profit sharing plans. The economic effect for Active AM Accounts ($Dummy(AM_i0)$) is 17% (20%) of unconditional mean. Those results suggest that AM firms have greater fractions of variable pay. Unreported results also show that AM companies tend to have higher diversity both in their boards and workforce. As a whole, those positive traits are consistent with more creative cultures and firms that attract less risk-averse employees. We will discuss those positive traits later

¹⁶As a reminder, this variable is coded as a negative number if the company is involved with the regimes that violate human rights, violate right of indigenous people, or are involved in labor disputes and anti-union policies. It is coded as positive if company has proactive policies to prevent such involvement, have pro-indigenous people policies and is pro-labor-unions. Unreported results showed that what we observe in Specification 5 is driven by mostly violations rather than strong anti-human rights violations policies.

¹⁷Unreported results showed that what we observe in Specification 7 and 8 is driven by mostly product quality concerns rather than product quality strength.

in the section devoted to innovations.

Panel B of Table 5 reports the results for matching sample. Matching procedure was discussed previously. The results generally agree with the one reported. Out of five KLD variables, only in one test (for Product Quality variable) we failed to reject the equivalence in AM sample and matched sample. For example, Bribery and Fraud is actually 57% larger than the realization of the same variable in zero-AM matched sample. Remarkably, it is very close to economic effect reported in Panel A. Tax Disputes in AM sample is actually three times larger than in zero-AM sample. AM-firms has 69% worst realization of Human Rights Violations variable. Finally, AM-firms are 66% more likely to be involved in profit sharing programs.

Finally we will look at the data on use of tax havens and tax avoidance. Dyreng and Lindsey (2009) build the list of all countries mentioned in 10-K forms (Exhibit 21). We use the proportion of tax havens among the countries the firm is dealing with. We assume that there is unlikely that the company would have a legitimate reason to deal in its international business with predominately tax havens. We use three cutoffs, 50% (i.e., more than half of the countries the firm is doing business in are tax havens), 75%, and 90%. Table 6, Panel A, reports the results for use of tax havens. Even in weakest test (50% cutoff, reported in Specification 1 and 2), the effect of AM membership is both economically and statistically significant. One standard deviation of Active AM Accounts leads to 0.32% higher probability of abnormal tax havens' use by the firm. That represents 6% increase of unconditional probability of use of tax havens. Similar estimate for $Dummy(AM_{\hat{\delta}0})$ leads to 11% increase with respect to unconditional mean. For 90% cutoff (reported in Specifications 5 and 6), the effect is considerably larger. For Active AM Accounts ($Dummy(AM_{\hat{\delta}0})$) it represents 14% (34%) increase with respect of unconditional mean. Among other variables, presense of institutional investors, competitive environment, higher valuation as measured by Tobin's Q, and larger market capitalization lead to increase in use of tax havens, whereas family firms tend to use tax havens less.

We also look at effective tax rate (defined as tax expense divided by pretax income, results reported in Table 6, Panel B). Even after controlling for use of tax havens use, effective tax rate is about 0.16% lower for AM companies (it represents about 1.1% of overall tax bill. The results for $Dummy(AM_{\hat{\delta}0})$ reported in specifications 2,4, and 6, are not significant at 10% level, however, they are of negative sign and similar magnitude to the estimates reported for Active AM Accounts.

Taken together, those results document strong association between number of mostly negative corporate behavioral traits and Ashley Madison membership by corporate employees.

3.2 Creativity and Integrity

Research in psychology and behavioral economics finds a robust positive association between dishonesty and creativity. Gino and Ariely (2012) find that creativity is an even stronger determinant of unethical behavior than intelligence in an experimental setting. They argue that this is because both creativity and unethical behavior are based on patterns of thinking that involve breaking existing rules. Creative people may also be more able to develop rationalizations for unethical behavior. In a controlled experiment, Gino and Wiltermuth (2014) find that acting dishonestly leads to greater creativity in subsequent tasks within the same individual. They argue that acting dishonestly leads to "... a heightened feeling of being unconstrained by rules" (Gino and Wiltermuth (2014)).

Financial history is replete with examples of the connections between creativity and unethical behavior. Bernie Madoff, Bernard Ebbers, Kenneth Lay, and Michael Milken are just a few examples of individuals who were considered very creative and were caught behaving unethically.¹⁸ This is not to say that creative people cannot be ethical. History is also filled with very creative people with the highest measures of integrity. Leo Tolstoy is extolled to be a creative person because of his writing, philosophy, and leadership, and is also commonly considered to personify a moral compass. However, in a competitive environment, even a mild association between creativity and unethical behavior can propagate into consequential outcomes for firms that select on creative employees. If competition is high and ingenuity is important, then firms may have to relax their standards and hire employees with potentially compromised ethics in order to keep up in an arms race with creative rivals.

We expand on the economics and psychology literature by testing the direction (and the existence) of an association between creativity and dishonesty at the firm level. Since we do not have a direct measure for creativity, we use successful patent applications and subsequent citations,

¹⁸For example, Weiner (2005) praised the technology developed by Bernie Madoff that eventually became NASDAQ. Weiner, Eric J. (2005). "Lay turned a sleepy natural gas pipeline group into a model of new age capitalism", CBS News/AP, July 5, 2006. "Milken was a key source of the organizational changes that have impelled economic growth over the last twenty years. Most striking was the productivity surge in capital, as Milken...and others took the vast sums trapped in old-line businesses and put them back into the markets." Gilder (2000)

patent portfolio diversity, R&D success, and R&D intensity as proxies for creativity at the firm level. Creativity is defined as the ability to make new things or think of new ideas. A patent is an exclusive right to a new device or method in exchange for disclosure of information regarding the invention. In order for a patent to be granted, an invention must be proven to be novel, useful, and non-obvious. An external patent reviewer is responsible for determining whether a patent application has met these criteria. Thus, creativity is a crucial determinant of successfully securing a patent. Furthermore, subsequent citations provide a measure of patent success, which to a large extent, depends on the degree of novelty and usefulness of a patent (Hall, Jaffe, and Trajtenberg, 2001).

Table ?? presents results of tobit regressions of several measures of innovation on AshleyMadison membership. First, we examine the effect of AM membership on innovation at the extensive margin (Panel A of Table ??). Specifically, we find that a one standard deviation increase in AM membership (presence of AM members within the firm) is associated with a 23% (37%) increase in *Patents*, the number of propensity and truncation adjusted patents filed by the firm. Similarly, firms spend more on R&D in absolute numbers (Specifications 3 and 4 of Panel A), and spend more relative to sales, $R\&D/sales_{t-1}$ (Specifications 5 and 6). For the former, the economic effect of one standard deviation of Active AM Accounts ($Dummy(AM_{i0})$) is equivalent to 14.9% (11.7%) increase in R&D, for the latter the similar effect is 13.1% (8.5%). The results in Specifications 1-6 imply that firms with higher AM membership issue more successful patent applications and spend more on research and development effort. However, it could be the case that these firms also spend significantly more resources to achieve the additional patent grants, suggesting that these firms are not necessarily more creative in an efficient manner. Therefore, we turn to measures of innovation intensity and success as measures of creativity. Specifications 7 and 8 show us that it is not just spending more money on research that matters for patent results, it is actually getting more patents out of each dollar spent. $Patents/R\&D$ for AM firms with one standard deviation higher Active AM Accounts (presence of AM accounts as measured by $Dummy(AM_{i0})$) increase by 28.4% (71.4%) of unconditional mean.

Is it possible that firms are perfecting the art of obtaining useless and inconsequential patents? Panel B of Table ?? looks at the issue of quality and diversity of the patents. In Specifications 1 and 2, we look at Citations per Patent, $Citesperpat$. One standard deviation increase in Active AM

Accounts (presence of AM accounts as measured by $Dummy(AM_{i0})$) leads to increase in $Citesperpat$ by 19.8% (30.3%) of unconditional mean. Specifications 3 and 4 showed that this is not just citations that matters, but those citations are achieved by spending less dollars per cite on research and development. The economic effect is significant 24.3% (52.9%) increase from unconditional mean as measured by one standard deviation of Active AM Accounts ($Dummy(AM_{i0})$).

Finally, we look at *Patent Diversity* (Specifications 5-8 in Panel B). Being creative involves a willingness to bend the rules and “think outside the box.” Therefore, we posit that, all else equal, a more creative firm will not constrain itself to patent within a particular set of narrow patent technology classes, but will instead patent in a variety of areas. To isolate the interpretation of creativity and not investment opportunities, we control for Tobin’s Q. That is, holding fixed the investment opportunities for a firm, higher AM membership is associated with patenting in a wider variety of patent technology classes. A one standard deviation increase in *Active AM Accounts* ($Dummy(AM_{i0})$) increases patent diversity by 12% (19.8%) of unconditional mean. The results for Citation Diversity are similar. Thus, firms with higher AM membership is producing more diverse patents, and those patents are important outside of one single category ¹⁹.

For robustness, we also looked at matched firms. The results are reported in Panel C. In all metrics but one the differences are statistically and economically significant ²⁰. In terms of Patents (Citations), the difference is 30% (27%) of the mean for zero-AM groups. For other variables, the differences are within 20-30% range.

3.3 Inventor Analysis and Quasi-Experimental Evidence

So far, our results are consistent with firms selecting employees (and vice versa) to fit their culture. However, what happens if a firm’s culture suddenly changes? Do innovative employees become relatively less innovative or risk taking if the culture becomes more rules-based and potentially constraining? In this section, we explore quasi-experimental evidence to investigate a potential causal relation between culture and creativity.

Specifically, we exploit shocks to culture coming from mergers to study the impact on the

¹⁹We also used Adjusted Citations Diversity. The results for it are similar to the results for Citations Diversity and are omitted for brevity.

²⁰The difference for *Patents/R&D* is economically significant at 27% larger mean for AM companies than for zero-AM companies, but *p-value* is only 0.11.

innovation of individual inventors listed in the Harvard Patent Database inventor file (Li, Lai, DAmour, Doolin, Sun, Torvik, Yu, and Fleming, 2014). We focus on serial inventors (i.e. those that file patents in at least different two years in the sample) who work for target firms prior to a merger.²¹ Since we only track inventors that we can observe both pre- and post-merger, we are able to exclude potential explanations driven by the selection of new employees into particular kinds of firms based on the new, post-merger culture.

The decision to merge is not exogenous to a firm's senior management. For example, less innovative firms may choose to acquire more innovative firms in order to promote technological development. However, for large Compustat-listed firms, it is unlikely that individual inventors, especially those employed at the target firms, play a large role in merger decisions. Thus, mergers seem to provide a useful source of quasi-exogenous variation in culture to study the effect on innovative activity within a given inventor employed at a target firm. Of course, it is possible that very successful inventors are important enough within some targets to drive some of the merger activity that we observe. Therefore, if innovative output is mean reverting within individuals, we might expect innovation for those individuals to fall after such mergers. However, it is hard to imagine plausible stories which suggest that the mean reverting process is directly dependent on the AM intensity of the acquiring firms. For this reason, we exploit cross-sectional differences in acquirer culture in two difference-in-differences frameworks, which precludes explanations that predict a uniform decline in patenting post-merger (e.g. due to mean-reversion in patenting). Thus, a causal interpretation in our setting requires that acquirer firm AM membership intensity is exogenous to inventors that file patents in publicly-listed target companies.

First, we classify acquirers as low (high) AM cultures if they are below (above) the median AM membership in a given year. We use this classification to measure the differential impact on innovation between inventors acquired by strict and lax cultures. The first four specifications in Table 8 report these results. We find evidence that innovation decreases significantly, both economically and statistically, for a given inventor after being acquired by a low AM culture. In particular, being acquired by a low AM culture results in 0.134 fewer patents per year and 0.31 fewer citations per patent, representing 7.4% and 34% of the unconditional means, respectively.

²¹We only focus on publicly traded targets so that we can track pre-merger inventor relationships with the target. Also, since the AshleyMadison data is only available starting in 2002, and the quality of the patent data begins to deteriorate rapidly after 2006 due to truncation issues, we focus on mergers that occur in 2002-2006.

Thus, acquisitions by low AM firms appear to stifle innovation by a greater extent.

Second, we recognize that it may be the culture of the acquirer relative to that of the target, which is relevant for a shock to inventor culture. For example, if a target with a strict culture is acquired by a similarly strict culture, then we might not expect the merger to have a meaningful effect. We define a shock as tightening (relaxing) culture if the relative differences between the acquirer and target AM intensities (AM membership scaled by total assets) is negative (positive). Thus, a tightening of culture would indicate that a target was acquired by firm with relatively less intense AM membership.²² In these specifications (5–8) we find that a relative tightening of culture also results in lower innovation for a given inventor. Specifically, being acquired by a relatively tighter culture results in 0.55 fewer patents per year and 0.175 fewer citations per patent, representing 30% and 19% of the unconditional means, respectively. These results provide some evidence that the relationship between culture and creativity may be causal.

3.4 Internal vs. External CEOs

In this section, we ask the question: Do firms make an attempt to transform a culture with low integrity? Prior literature suggests that culture is one the most difficult organizational attributes to change; it outlasts organizational products, services, founders, leadership, and the physical attributes of an organization (Schein, 1992). However, as the firm’s business environment changes, its former culture may no longer be appropriate. “When basic survival is threatened in terms of an organization’s ultimate mission, there is a very strong external impetus to make a radical change in culture.” (Flanagan, 1995). Research in management science has suggested that such a transformation often begins when an organization has a new, strong leader who understands the need for a major change (Kotter, 1995). This literature also recommends that such firms should hire CEOs from outside the firm—or even outside the industry—if changing the existing culture is a primary goal (Bailey and Helfat, 2003).²³

²²In unreported results, we define tightening (relaxing) as targets with non-zero (zero) AM membership being acquired by firms with zero (non-zero) AM membership and find similar results. We also find similar results when we scale AM membership by the number of employees, rather than assets, to calculate the relative intensities.

²³Lou Gerstner, the former IBM CEO is an example of an outsider who was brought in to change the corporate culture (and succeeded). Many attempts to replicate this story have failed. For example, Hewlett-Packard’s Carly Fiorina and Procter & Gamble’s Durk Jager, are cited as examples of CEOs that tried to change too much, too soon. Research has documented that many outside CEOs have not made meaningful changes at all (Karaevli and Zajac, 2013).

Thus, the literature suggests that if a firm wants to change its culture, an effective way to do so is to hire an external CEO. In our context, we ask whether firms with high levels of AM membership attempt to change their culture in this manner. This would be the case if there were no trade-offs to consider in the attempt to enforce stricter standards of integrity. We exploit CEO changes to examine whether firms with high AM membership are more likely to hire external CEOs. We acknowledge that firm culture may be difficult to change, and therefore we do not attempt to measure the success or failure of a regime shift. However, a firm trying to institute a deep cultural shift is more likely to do so by appointing an external CEO rather than by hiring someone who has been a part of the very culture the firm is trying to change.

We use Boardex data from 2003-2013 to identify internal versus external CEO hires. We define internal CEOs as CEOs who were employed at the hiring firm for at least two years before their appointment. Table 8 presents the results from our analysis. The unconditional probability of hiring internal CEOs in our sample is 0.378. After controlling for time effects as well as industry and geography fixed effects, the probability of choosing an internal CEO is significantly higher for firms with higher AM membership. Specifically, a one standard deviation increase in the number of AM accounts leads to a 6.9-14.4% increase in the probability that a new CEO appointment comes from within the firm, or between 18-38% of the unconditional probability. These results are consistent with Fiordelisi and Ricci (2014), who show that companies with more creative cultures are more likely to choose an internal CEO in order to continue their success. Furthermore, our evidence suggests that firms (i.e., boards of directors) are content with a culture that supports a relatively high level of AM membership. This is consistent with our hypothesis that there are inherent trade-offs to engineering a corporate culture. These results are also consistent with those of Parrino (1997).²⁴

²⁴In unreported tests, we examine whether CEO characteristics can explain our results. In particular, we examine the overconfidence measure in Malmendier and Tate (2005). We construct the backward-looking measure, *Holder 67*, that describes the exercise decision of a CEO in the fifth year prior to expiration. Five years before expiration is the earliest point we can consider since most options in our sample have a ten-year duration and are fully vested only after year four. Under Malmendier and Tate (2005) assumptions of constant relative risk aversion and diversification, the new exercise threshold in the Hall-Murphy framework is 67%. We set *Holder 67* equal to 1 if a CEO fails to exercise options with five years remaining duration despite a 67% increase in stock price (or more) since the grant date. We find no correlation between *Holder 67* and Active AM Accounts (it is 0.026). We do not see any significant changes in the coefficient on our variable of interest in all regressions in our paper after controlling for CEO overconfidence, age, and gender.

4 Conclusion

We find that individual decisions by employees of a firm provides a great deal of information about the firm that employs them. Firms that have a greater number of employees registered on AshleyMadison are not only more likely to behave more unethically, they are also likely be more innovative and risk-taking.

Our results are consistent with the hypothesis that firms where innovation and risk taking are important have cultures that enable this behavior. Such firms attract, select, and retain employees whose personalities best match the firms' culture. The interesting insight is that the same characteristic (i.e., AM membership) predicts unethical behavior, risk-taking, and innovation. One interpretation is that the firms where creativity and innovation are important focus on these personality traits when selecting and evaluating employees, and they do not screen as carefully for high ethical standards. Another interpretation is that creativity and a lack of ethics are correlated traits as shown by Gino and Ariely (2012) and Gino and Wiltermuth (2014). Creative and innovative firms select creative and risk-taking applicants. However when they do so, they hire a composite package that is more likely to contain ethical imperfections as well.

We also provide preliminary evidence regarding the causal nature of the relationship between culture and creativity. Specifically, we track individual inventors of target firms pre- and post-merger, using the culture of the acquiring firm as a shock to an inventor's culture. While mergers are endogenously chosen by upper management of a firm, they provide a useful source of plausibly exogenous variation in culture for a given target-firm inventor who is unlikely to play a large role in merger decisions. We find that post-merger innovation is hindered when inventors are acquired by firms strict cultures, both in an absolute sense and relative to the culture of the target. These results increase our confidence that we have identified a true meaningful underlying positive relation between culture and creativity and provides some evidence that the relationship may be causal.

Overall, our results suggest that the personality traits of employees vary systematically across firms. Firm culture is related to corporate outcomes, and firms and employees tend to have matching personality types. We also find some evidence of a causal link between culture and a specific firm outcome: patenting activity of serial inventors.

An interesting avenue for further research is understand whether a causal relation extends

to more general settings. Research argues that culture fits the firm's business environment, and employee personalities are selected to fit the culture. Yet, research also argues that the corporate culture is persistent. Thus, rapid changes in the firm's external environment might lead to a culture that is no longer suited to the firm's environment. Are such firms the proverbial "dinosaurs" that cannot adapt to changes in their environment and thus go extinct? Anecdotal evidence suggests that even CEOs find it difficult to change a firm's culture.

For example, Schwartz and Davis (1981) discuss the case of Walter Spencer, the former CEO of Sherwin-Williams:

"Speaking of his attempt to transform Sherwin-Williams from a production-oriented company to a marketing-oriented one. Spencer said, "When you take a 100-year-old company and change the culture of the organization, and try to do that in Cleveland's traditional business setting well, it takes time. You just have to keep hammering away at everybody." After six years of such "hammering away," Spencer resigned, saying the job was no longer any fun. He had dented but not changed the culture."

Sherwin-Williams survived the changes in its external environment in the 1980s, by perhaps eventually successfully changing its culture. But was it the exception, rather than the rule? Are firms with cultures that do not match their current environment more likely to exhibit adverse performance? Or, in other words, does culture have a causal effect on firm performance in general?

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Table 1: Descriptive Statistics

This table presents summary statistics for AshleyMadison (AM) variables (panel A), as well as the other variables used in our analysis. The AM data cover the sample period 2002-2014. We report the number of observations, means, standard deviations, and the 10th and 90th percentiles for each variable. All definitions are provided in detail in the appendix.

Variable	Mean	σ	10pct	90pct	N	Variable	Mean	σ	10pct	90pct	N
Panel A: AshleyMadison											
Active AM Accounts											
all firms	2.052	12.130	0.000	4.000	34961	Bribery and Fraud	0.047	0.212	0.000	0.000	3428
firms \geq 1 account	5.391	19.200	0.000	10.000	13306	Human Rights Violations	-0.032	0.262	0.000	0.000	18090
Average Years of Activity	0.712	1.105	0.000	2.000	13303	Tax Disputes	0.021	0.143	0.000	0.000	11168
Average Age of AM User	39.238	7.659	30.000	49.000	13231	Cash/Stock Sharing	0.144	0.403	0.000	1.000	14095
Average Credits	0.169	6.562	0.000	0.000	11560	Product Quality	-0.018	0.294	0.000	0.000	18096
Panel B: Firm and Industry Characteristics											
Book Leverage	0.227	0.254	0.000	0.577	40712	Panel C: AAER data					
Debt/Market Equity	0.645	1.923	0.000	1.281	40712	Misstatement	0.007	0.083	0.000	0.000	40712
Log Market Cap	5.490	2.312	2.420	8.416	40712	Panel F: Patent data					
Tobin's Q	2.575	3.131	0.953	4.631	40712	Ln(R&D)	1.400	1.798	0.000	4.108	40712
Market to Book Ratio	2.719	6.465	0.202	6.665	40712	Patent Cites	0.079	0.307	0.000	0.000	32666
ROA	-0.042	0.593	-0.385	0.259	40712	Patents	0.051	0.259	0.000	0.000	32666
Tangibility	0.233	0.228	0.025	0.604	40712	Pat/R&D	0.006	0.137	0.000	0.000	14121
# of Employee	8.564	38.860	0.035	17.000	40712	Top 10	0.023	1.455	0.000	0.000	32666
Firm Age	17.306	12.266	5.000	37.000	39056	Pdiv	0.043	0.182	0.000	0.000	32666
Log Sales	5.152	2.626	1.694	8.333	40712	Cdiv	0.043	0.183	0.000	0.000	32666
Cash/Asset	0.227	0.235	0.014	0.604	40712	ACdiv	0.043	0.183	0.000	0.000	32666
Volatility-3 Factor adjusted	0.027	0.012	0.013	0.044	34247						
HHI(sic4)	0.122	0.176	0.001	0.337	40712						
Stock Return	0.126	0.533	-0.486	0.753	34252						
Skewness	0.368	0.742	-0.372	1.119	33982						
CDS Spread	0.026	0.076	0.003	0.050	4262						

Table 2: AshleyMadison by Industry and MSA

Panels A and B report the top ten and bottom ten Fama-French 49 industries, respectively, ranked by the annual sum of the number of active AshleyMadison (AM) accounts for all firms within that industry. Panel C reports the top ten Economic Areas (EAs), defined by the Bureau of Economic Analysis, ranked by the annual average number of active accounts per million residents. We report the primary city and BEA code for each EA.

Panel A - Top 10 Industries.			
Rank	Industry	AM Accounts	
1	Computer Software	663.423	
2	Transportation	579	
3	Electronic Equipment	361.429	
4	Automobiles and Trucks	353.767	
5	Retail	336.571	
6	Computers	279.18	
7	Business Services	278.329	
8	Petroleum and Natural Gas	272.907	
9	Chemicals	216.164	
10	Communication	297.495	
Panel B - Bottom 10 Industries			
Rank	Industry	AM Accounts	
1	Fabricated Products	1.415	
2	Defense	3.824	
3	Non-Metallic and Industrial Metal Mining	4.224	
4	Tobacco Products	6.547	
5	Shipbuilding, Railroad Equipment	6.696	
6	Textiles	6.711	
7	Beer & Liquor	8.220	
8	Rubber and Plastic Products	11.196	
9	Coal	11.755	
10	Precious Metals	12.815	
Panel C - Top 10 EAs (per 1 million residents)			
Rank	Area	BEA Code	AM Account
1	Appleton-Oshkosh-Neenah	9	874.503
2	Wichita-Winfield	179	820.846
3	Memphis, TN-MS-AR	105	557.668
4	Anchorage	8	386.253
5	Detroit-Warren-Flint, MI	47	355.77
6	Little Rock-North Little Rock-Pine Bluff, AR	96	350.972
7	Cincinnati-Middletown-Wilmington, OH-KY-IN	33	347.895
8	Seattle-Tacoma-Olympia, WA	152	307.570
9	Cedar Rapids, IA	27	271.820
10	Champaign-Urbana	28	218.662

Table 3: AAER Misstatements and AshleyMadison Membership

In Panel A, we report coefficient estimates and marginal effects for logistic regressions of accounting misstatements on the number of active AshleyMadison (AM) accounts. Data on misstatements and specification from 2002-2014 come from the AAER dataset discussed in Dechow, Ge, Larson, and Sloan (2011). This dataset provides detailed information regarding misstatement investigations for public corporations. Specification 1, 3, and 5 reports estimates for logarithm of number of AM accounts, while Specifications 2,4, and 6 use dummy equal to one if number of AM accounts exceeds one, and zero otherwise. We include four accruals-related measures. *WC accruals*, focuses on working capital accruals and is described in Allen, Larson, and Sloan (2009). *RSST accruals* are defined in Richardson et al (2005) and Dechow et al (2011) and extends the definition of WC accruals to include changes in long term operating assets and liabilities. *Change in receivables* (*Change in inventory* is defined in Dechow et al (2011) as change in accounts receivables (inventory) normalized by average total assets. *Soft Assets* is defined in Barton and Simko (2002) as Total Assets minus PP&E minus Cash and Cash Equivalent normalized by Total Assets. Performance variables include *Change in cash sales* (defined as percentage change in sales minus change in Accounts receivables), *Change in cash margin* (defined as percentage change), and *Change in ROA* (defined as ROA(t) minus ROA(t-1)). *Actual Issuance* is a dummy equal to one if the firm issued securities during year t, and zero otherwise. Specifications (3) and (4) contains also *Abnormal change in employees* (defined as percentage change in the number of employees minus percentage change in assets), and *Dummy Lease* (defined as one if future operating lease obligations are greater than zero, and zero otherwise). Specifications (5) and (6) also used current and lagged market-adjusted stock return and logarithm of number of employees. *(Lagged) market-adjusted stock return* is (previous year) annual buy-and-hold returns minus buy-and-hold CRSP value-weighted index returns. All specifications include year and industry fixed effects, and all dependent variables are lagged by one year. The t-statistics, calculated from standard errors clustered at the year level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. Marginal effects are reported below the estimates in square brackets, and are multiplied by 100. In Panel B, we report matching-sample estimate of a difference between misstatement in AM-sample and matched sample with zero AM accounts. We report mean in both AM-sample (sample with number of accounts greater than zero), and matched sample, the difference between the two, number of matched pairs, t-statistics and p-value of t-test (clustered over).

Table 3: AAER Misstatements and AshleyMadison Membership

Panel A: Regression						
	(1)	(2)	(3)	(4)	(5)	(6)
Active AM Account	0.390 *** [0.658] (4.18)		0.383 *** [0.656] (4.02)		0.249 * [0.447] (1.87)	
Dummy(AM>0)		0.628 *** [1.06] (7.98)		0.612 *** [1.048] (7.49)		0.469 *** [0.842] (4.66)
RSST Accruals	0.139 *** [0.234] (4.1)	0.139 *** [0.235] (4.38)	0.139 *** [0.238] (4.72)	0.140 *** [0.24] (4.81)	-0.515 * [-0.924] (-1.82)	-0.535 * [-0.959] (-1.85)
Change in receivables	-1.435 [-2.422] (-1.31)	-1.420 [-2.397] (-1.24)	-1.595 [-2.73] (-1.4)	-1.571 [-2.69] (-1.32)	-2.365 *** [-4.241] (-3.49)	-2.374 *** [-4.256] (-3.35)
Change in inventory	2.156 [3.64] (1.47)	2.149 [3.629] (1.46)	2.153 [3.684] (1.45)	2.142 [3.666] (1.44)	3.336 *** [5.982] (3.1)	3.364 *** [6.03] (3.23)
% Soft assets	1.931 *** [3.259] (6.65)	1.977 *** [3.338] (7.13)	1.945 *** [3.328] (6.66)	1.990 *** [3.407] (7.09)	2.407 *** [4.317] (5.7)	2.451 *** [4.394] (6)
Change in cash sales	0.000 *** [0.000] (-3.96)	0.000 *** [0.000] (-3.95)	0.000 *** [0.000] (-3.81)	0.000 *** [0.000] (-3.82)	0.000 *** [0.000] (-5.29)	0.000 *** [0.000] (-5.2)
Change in ROA	-0.010 *** [-0.016] (-2.92)	-0.009 *** [-0.016] (-2.79)	-0.010 *** [-0.018] (-3.04)	-0.010 *** [-0.017] (-2.81)	0.115 [0.207] (0.47)	0.119 [0.213] (0.48)
Change in cash margin	0.000 *** [0.000] (4.52)	0.000 *** [0.000] (4.31)	0.000 *** [0.000] (4.1)	0.000 *** [0.000] (4.08)	0.000 *** [0.000] (4.92)	0.000 *** [0.000] (4.84)
Actual issuance	0.802 * [1.353] (1.87)	0.790 * [1.334] (1.79)	0.817 * [1.398] (1.88)	0.808 * [1.383] (1.81)	0.720 [1.291] (1.04)	0.724 [1.297] (1.00)
Abnormal change in employees			-0.071 [-0.121] (-0.55)	-0.065 [-0.111] (-0.54)	-0.287 * [-0.515] (-1.84)	-0.301 * [-0.54] (-1.92)
Existence of operating leases			-0.449 [-0.768] (-0.38)	-0.466 [-0.797] (-0.39)	-2.555 *** [-4.583] (-2.79)	-2.603 *** [-4.667] (-2.78)
Market adjusted stock return t					0.297 [0.532] (0.92)	0.286 [0.513] (0.88)
Market adjusted stock return t_{-1}					0.306 [0.549] (1.26)	0.295 [0.529] (1.24)
Log # of employees					0.119 *** [0.213] (2.63)	0.127 *** [0.227] (4.00)
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Pseudo R-Square	0.194	0.194	0.196	0.196	0.219	0.220
Observations	27775	27775	27325	27325	22557	22557
Panel B: Matched Sample						
Misstatement	Mean (AM)	Mean (Matched)	Δ_{Mean}	Number of Matched Pairs	t-stat	P-Value
	1.186	0.678	0.508	4132	1.780	0.075

Table 5: Tax and AshleyMadison Membership

In Panel A, we use the dummy equal to one if proportion of tax havens among countries mentioned in Exhibit 21 of their 10-K filing exceeds 50% (75%, 90%). We use data maintained by Dyreng and Lindsey (described in Dyreng and Lindsey, 2009). They download every 10-K available on SEC between 1994 and 2014 and search every 10-K filing (Exhibit 21) for country names. Countries are identified as tax havens if they are defined as such by three of the four following sources: (1) Organization for Economic Cooperation and Development (OECD), (2) the U.S. Stop Tax Havens Abuse Act, (3) The International Monetary Fund (IMF), and (4) the Tax Research Organization. We define mostly_txh50 (mostly_txh75, mostly_txh90) as a dummy equal to one, if more than 50% (75%, 90%) of the countries mentioned in 10-K filings are tax havens, and zero otherwise. We report marginal effects (multiplied by 100) of the probit regression and t-statistics in parentheses. Standard errors were clustered over time. All estimates are done with industry, year, and EA fixed effects. In Panel B, we report regressions for Effective Tax Rate, calculated using income tax divided by pretax income excluding special items. All estimates are multiplied by 100. t-statistics is reported in parentheses. Standard errors were clustered over time. All estimates are done with industry, year, and EA fixed effects. All variables are defined in the appendix and within the text. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

Panel A: Regression						
	(1)	(2)	(3)	(4)	(5)	(6)
	MostlyTxh50	MostlyTxh50	MostlyTxh75	MostlyTxh75	MostlyTxh90	MostlyTxh90
Active AM Account	0.317 *** (3.68)		0.519 *** (4.43)		0.541 *** (4.44)	
Dummy(AM>0)		0.637 ** (2.16)		1.225 *** (5.27)		1.353 *** (5.37)
Institutional Investor	2.023 *** (4.48)	1.941 *** (4.35)	1.633 *** (4.02)	1.490 *** (3.96)	1.503 *** (4.14)	1.373 *** (4.2)
HHI (SIC4)	-4.316 *** (-5.34)	-4.230 *** (-4.98)	-3.035 *** (-4.62)	-3.026 *** (-4.83)	-2.460 *** (-4.48)	-2.411 *** (-4.65)
Market Cap (t-1)	1.032 *** (5.01)	1.004 *** (4.98)	0.322 *** (2.85)	0.323 *** (2.74)	0.273 *** (2.64)	0.263 *** (2.48)
Log # of Employee	-0.718 *** (-2.76)	-0.581 ** (-2.14)	-0.304 * (-1.71)	-0.197 (-1.06)	-0.262 (-1.58)	-0.154 (-0.9)
EBITDA/Assets	-6.485 *** (-3.14)	-6.764 *** (-3.55)	-1.056 (-0.83)	-1.332 (-1.15)	-1.257 (-1.07)	-1.499 (-1.4)
Tobin's Q (t-1)	0.281 * (1.91)	0.251 * (1.76)	0.389 *** (4.73)	0.375 *** (4.57)	0.325 *** (4.03)	0.312 *** (3.88)
Family Firm	-2.008 *** (-4.5)	-1.807 *** (-4.01)	-1.742 *** (-3.74)	-1.552 *** (-3.43)	-1.533 *** (-3.47)	-1.344 *** (-3.19)
GIndex	-0.131 ** (-2.12)	-0.073 (-1.02)	-0.001 (-0.03)	0.015 (0.36)	0.002 (0.05)	0.015 (0.41)
EA FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Industry(SIC2) FE	✓	✓	✓	✓	✓	✓
Observations	6315	6315	5506	5506	5124	5124
Pseudo R2	0.191	0.181	0.191	0.189	0.206	0.205

Table 6: Corporate Innovation and AshleyMadison Membership

In Panel A we report tobit estimates for the association between the number of active AshleyMadison (AM) accounts and measures of firm-level innovation intensity. We look at common measures of innovation using patent data from 2002-2005. Specifically, we look at Patents (Specifications 1 and 2), R&D (Specifications 3 and 4), R&D/Sales (Specifications 5 and 6), and patents scaled by R&D expenses (Specifications 7 and 8). In Panel B, we report tobit estimates for the association between the number of active AshleyMadison (AM) accounts and measures of firm-level innovation quality. Specifications 1 and 2 reports the results for adjusted patent citations, specifications 3 and 4 reports the results for Citations/R&D, specifications 5 and 6 (7 and 8) reports the results for Patents Diversity (Citations Diversity). Our regressors of interest are the natural logarithm of one plus the number of active AM accounts for a given firm year (even specifications), and dummy that is equal to one if AM Accounts is greater than zero, and zero otherwise. All specifications include year, industry (2 digit sic code), and EA fixed effects. All regressors are lagged one year relative to our innovation measures. All variables are defined in the appendix and within the text. The t-statistics, calculated from standard errors clustered at the industry level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. Panel C reports matching sample estimates for main innovation intensity and quality variables.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent	Patent	R&D	R&D	R&D/Sales	R&D/Sales	Patents/R&D	Patents/R&D
Active AM Account (t-1)	0.450*** (35.53)		0.174*** (14.94)		0.0216*** (14.33)		0.0222*** (24.45)	
Dummy(AM>0)		0.565*** (27.50)		0.111*** (7.695)		0.0106*** (6.401)		0.0430*** (30.74)
Size	0.530*** (200.1)	0.567*** (210.1)	0.420*** (283.5)	0.430*** (306.1)	-0.0681*** (-576.9)	-0.0666*** (-537.0)	0.0102*** (60.12)	0.0119*** (68.00)
Age	-0.0235*** (-32.27)	-0.0220*** (-30.35)	0.000805*** (3.246)	0.00121*** (5.112)	-0.000685*** (-43.21)	-0.000628*** (-38.75)	-0.00319*** (-40.72)	-0.00312*** (-39.59)
Market to Book	0.0402*** (40.96)	0.0423*** (47.58)	-8.94e-05*** (-49.61)	-9.06e-05*** (-51.24)	9.98e-07*** (3.612)	8.30e-07*** (3.040)	0.00181*** (36.41)	0.00190*** (41.18)
Cash	0.252*** (79.89)	0.252*** (79.89)	0.263*** (112.3)	0.264*** (118.6)	0.0282*** (101.1)	0.0283*** (96.16)	0.0135*** (66.55)	0.0130*** (62.29)
Log # of Employee	-0.171*** (-28.29)	-0.168*** (-31.69)	-0.182*** (-50.70)	-0.173*** (-58.21)	0.00781*** (30.47)	0.00904*** (36.84)	0.00537*** (6.259)	0.00412*** (4.738)
Sigma	2.814*** (425.8)	2.823*** (416.0)	1.380*** (771.6)	1.384*** (775.8)	0.216*** (1.259)	0.217*** (1.240)	0.205*** (443.4)	0.205*** (454.5)
EA FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry(SIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,708	18,708	18,708	18,708	18,708	18,708	9,667	9,667
Pseudo R-squared	0.320	0.319	0.365	0.364	0.905	0.903	0.570	0.571

Panel A: Patent and R&D

Table 6: Corporate Innovation and AshleyMadison Membership

Panel B: Citation and Diversity		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Citations	Citations	Citations/R&D	Citations/R&D	Citations/R&D	Patent Div	Patent Div	Citation Div	Citation Div	Adj Citation Div	Adj Citation Div
Active AM Account ($t-1$)	6.858*** (21.86)			0.0650*** (14.29)	0.121*** (24.51)	0.154*** (18.16)	0.117*** (23.46)	0.194*** (23.04)	0.117*** (23.54)	0.194*** (23.14)	
Dummy(AM>0)	8.083*** (15.79)		0.109*** (18.40)		0.196*** (307.1)	0.206*** (319.6)	0.220*** (325.8)	0.229*** (333.3)	0.219*** (322.6)	0.228*** (329.4)	
Size	9.837*** (163.7)	0.0253*** (36.64)	0.0305*** (46.25)	0.0106*** (307.1)	-0.0102*** (-81.80)	-0.00990*** (-75.94)	-0.00990*** (-75.63)	-0.00953*** (-73.09)	-0.00990*** (-76.14)	-0.00953*** (-73.46)	
Age	-0.377*** (-23.17)	-0.00670*** (-26.88)	-0.00644*** (-26.88)	0.00720*** (63.92)	0.0156*** (39.68)	0.0161*** (44.18)	0.0137*** (37.77)	0.0142*** (42.94)	0.0136*** (38.02)	0.0141*** (43.28)	
Market to Book	0.797*** (46.34)	0.827*** (51.80)	0.00695*** (57.92)	0.0444*** (68.18)	0.127*** (137.0)	0.127*** (141.9)	0.110*** (107.2)	0.108*** (105.9)	0.110*** (107.4)	0.109*** (105.9)	
Cash	4.815*** (65.35)	4.816*** (68.18)	0.0444*** (49.37)	0.0435*** (50.65)	-0.0688*** (-36.66)	-0.0668*** (-41.53)	-0.0891*** (-47.98)	-0.0912*** (-53.12)	-0.0887*** (-47.92)	-0.0908*** (-53.03)	
Log # of Employee	-2.724*** (-16.00)	-2.659*** (-19.76)	0.0158*** (5.473)	0.0130*** (4.561)	1.011*** (395.7)	1.013*** (379.2)	1.072*** (468.4)	1.072*** (455.9)	1.068*** (466.6)	1.068*** (453.5)	
Sigma	53.53*** (321.2)	53.64*** (319.3)	0.683*** (326.0)	0.683*** (334.3)							
EA FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry(SIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,708	18,708	18,708	18,708	18,708	18,708	18,708	18,708	18,708	18,708	18,708
Pseudo R-squared	0.219	0.219	0.425	0.425	0.414	0.413	0.390	0.390	0.390	0.390	0.390
Panel C: Matched Sample		Mean (AM)	Mean (Matched)	Δ Mean	Number of Matched Pairs	t-stat	P-Value				
Patent	2.548	1.96	0.588	4551	2.7	0.007					
R&D	183.765	147.367	36.399	6020	6.98	0.0001					
R&D/Sales	8.739	7.141	1.597	6020	2.75	0.006					
Patent/R&D	0.155	0.122	0.033	1622	1.6	0.1106					
Citation	21.577	17.05	4.528	4551	2.19	0.0291					
Patent Div	2.929	2.409	0.52	4551	2.05	0.0401					
Citation Div	2.842	2.395	0.447	4551	1.85	0.064					

Table 7: Inventor patenting after mergers conditional on AM membership

In this table we report OLS regressions of patenting activity for inventors around mergers. We restrict the sample to target firm serial inventors (those with at least 2 patents filed in the sample) that are involved in exactly 1 merger in the sample. Post is a dummy variable that is 1 in the post merger period for the inventor's firm. Low AM is dummy variable that is 1 if the AM membership of the acquirer is less than its median across firms that year. Tightening Culture is a dummy variable that is 1 if AM intensity (AM membership/Total Assets) for the target is greater than that for the acquirer. These regressions are run at the inventor level with year and inventor fixed effects. The sample period is 2002-2006, with mergers in 2003,2004, and 2005 (the inventor data end in 2006 and the AM data begin in 2003). T-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficients. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patents	Cites	Cites per Patent	Top10 Citation	Patents	Cites	Cites per Patent	Top10 Citation
Low AM \times Post Merger	-0.134 (-0.99)	-1.095*** (-3.60)	-0.307** (-2.43)	-0.0964*** (-3.46)				
Low AM	-0.042 (-0.77)	0.119 (0.72)	0.0645 (1.64)	-0.0144 (-1.12)				
Tightening Culture \times Post Merger					-0.554*** (-3.96)	-1.238*** (-3.42)	-0.175** (-2.06)	-0.0668*** (-3.14)
Tightening Culture					0.108* (1.79)	0.383** (2.40)	0.129*** (3.44)	-0.0325*** (-2.59)
Post Merger	-0.0384 (-1.14)	0.195* (1.90)	0.0576* (1.83)	0.0183*** (3.44)	-0.0142 (-0.44)	0.183* (1.82)	0.0414 (1.35)	0.0164*** (3.03)
Inventor FE	✓	✓	✓	✓	✓	✓	✓	✓
year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	16321	16321	16321	16321	16321	16321	16321	16321
R-Squared	0.488	0.421	0.312	0.272	0.488	0.421	0.312	0.272

Table 8: AshleyMadison Membership and the Choice of Internal vs. External CEO

In this table we report the marginal effects estimates from a probit regression of choosing an internal CEO (1) vs. external CEO (0) on the number of active AshleyMadison (AM) accounts and dummy variable equals 1 if active AshleyMadison (AM) accounts is larger than 0. The data on CEOs come from Boardex for 2003-2014. We define a CEO as internal if he/she was employed at a given company for at least one full year before being appointed as CEO. Our regressor of interest is the natural logarithm of one plus the number of active AM accounts for a given firm year. Specifications 1-4 include year fixed effects, column 3 includes industry (2 digit sic code) fixed effects, and column 4 includes industry and EA fixed effects. All regressors are lagged one year relative to our CEO appointment variables. All variables are defined in the appendix and within the text. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	isINCEO	isINCEO	isINCEO	isINCEO	isINCEO
Active AM Account	0.088*** (12.00)	0.087*** (10.18)	0.179*** (12.99)	0.563*** (11.30)	
Dummy(AM>0)					0.098 *** (4.94)
Dummy: Institutional Investor	0.066 (1.54)	0.003 (0.08)	0.136* (1.80)	-0.528*** (-9.71)	-0.003 (-0.07)
Shares held by insiders	-0.673*** (-8.88)	-0.673*** (-8.66)	-0.606*** (-5.66)	-0.394** (-2.22)	-0.677 *** (-9.54)
HHI (SIC4)	0.140*** (2.78)	0.132*** (2.60)	0.238*** (3.96)	1.415*** (7.72)	0.106 * (1.79)
Log Market Cap(t-1)	-0.078*** (-9.30)	-0.076*** (-7.61)	-0.062** (-2.55)	-0.032 (-0.76)	-0.052 *** (-5.49)
Log # of Employee	0.040*** (4.08)	0.039*** (3.87)	-0.046*** (-2.72)	-0.062* (-1.82)	0.047 *** (4.07)
Family Firm	0.149*** (2.96)	0.150*** (2.76)	-0.031 (-0.41)	0.235** (2.03)	0.193 *** (3.22)
ROA	-0.056 (-0.64)	-0.155 (-1.50)	0.204 (1.47)	-0.317 (-0.86)	-0.254 *** (-3.19)
Governance Index (Gompers, Ishii, Metrick)	-0.009** (-2.14)	-0.009** (-2.11)	-0.023** (-2.49)	-0.095*** (-8.34)	-0.004 (-1.00)
Founder is director	-0.030 (-1.27)	-0.021 (-0.79)	-0.082*** (-2.91)	-0.395*** (-6.05)	0.001 (0.07)
Tobin's Q (t-1)	0.072*** (5.42)	0.094*** (4.68)	0.039* (1.79)	-0.013 (-0.27)	0.087 *** (4.85)
Δ_{OROA}		0.126 (0.69)	-0.210 (-1.13)	-0.705** (-2.38)	0.161 (0.98)
Δ_{OROS}		-0.023*** (-7.76)	-0.016*** (-7.72)	-0.046** (-2.35)	-0.023 *** (-6.64)
Year FE	✓	✓	✓	✓	✓
2-digit SIC FE			✓	✓	✓
EA FE				✓	✓
Observations	991	991	886	727	727
Pseudo-R2	.068	.077	.171	.499	0.475

Fifty Shades of Corporate Culture
Internet Appendix

Table A.1: Description of the Variables

This table provides a detailed description of all variables used in our analysis. Our main variable of interest is the AshleyMadison Active Accounts (AM Active Accounts) defined as log of number of active accounts at the end of year t (plus one).

Variable	Description	Source
Panel A - AshleyMadison Variables		
$AMAccounts_{i,t}$	The total number of AM accounts for firm i in year t . An account does not have to have sent a message or purchased credits to be included in this calculation for a given year. That is, the account does not have to be <i>active</i> .	AshleyMadison
$ActiveAMAccounts_{i,t}$	The total number of active AM accounts for firm i in year t . An account is required to have sent a message or purchased credits to be included in this measure. If an account is deactivated, then it is excluded from the calculation in a given year, but still included up until the year of its deactivation. This is our main variable of interest throughout the text.	AshleyMadison
$AMMaxAccounts_i$	The maximum total number of $AMActiveAccounts_{i,t}$ for a given firm throughout the sample	AshleyMadison
$AMNewAccounts_{i,t}$	The total number of new AM accounts created by employees in firm i during year t .	AshleyMadison
$AverageCredits_i$	The average credit balance of accounts linked to firm i .	AshleyMadison
Panel B - Firm Financial Information		
$BookLeverage_{i,t}$	Total debt divided by book value of assets. $[(dltt+dlc)/at]$	Compustat
$Debt/MarketEquity_{i,t}$	Total debt divided by market value of equity. $[(dltt + dlc) / (prcc_f*csho)]$	Compustat
$R\&D/Sales$	R&D expenditures divided by sales. $[xrd/sale]$	Compustat
$Tobin'sQ_{i,t}$	Total asset minus book value of equity plus the market value of equity divided by total assets $[(at - ceq + me)/at]$	Compustat
$MarkettoBookratio_{i,t}$	Market value of firms' equity divided by the book value of equity, following Fama-French calculation of book equity $[prcc_f * csho / teq - preferred + txditc]$	Compustat
$ROA_{i,t}$	Return on Asset. $[oibdp/l.at]$	Compustat
$Tangibility_{i,t}$	Net Property, Plant and Equipment divided by total assets $[ppent/at]$	Compustat
$\#ofEmployee_{i,t}$	The natural log of the total number of employee $[\log(emp)]$	Compustat
$FirmAge_{i,t}$	Firm age reported in Compustat or the number of years firm is observed in Compustat	Compustat

Continued on next page...

... table A.1 continued

Variable	Description	Source
$LogSales_{i,t}$	Natural log of sales [$\log(\text{sale})$]	Compustat
$Cash/Asset_{i,t}$	Cash and short-term investment divided by Assets [$(\text{ch} + \text{ivst})/\text{at}$]	Compustat
$LogMarketCap_{i,t}$	Natural log of market cap [$\log(\text{csho} * \text{prcc.f})$]	Compustat
$HHI(\text{sic4})_{i,t}$	Herfindahl index based on sales within 4-digit SIC industries in year t	Compustat
$\Delta_{OROA}_{i,t}$	Difference between the average operating income scaled by total assets 3 years before and after New CEO was appointed	Compustat
$\Delta_{OROS}_{i,t}$	Difference between the average operating income scaled by sales 3 years before and after New CEO was appointed	Compustat
$Stockreturn_{i,t}$	Annual return computed from cumulative daily returns	CRSP
Vol	– Stock return volatility, calculated from Fama-French 3-factor adjusted returns	CRSP
$3Factoradjusted_{i,t}$		
$skewness$	Skewness of Fama-French 3-factor adjusted returns	CRSP
Panel C - Ethics Variables		
$Bribery\ and\ Fraud$	A discrete variable that indicates the severity of controversies related to a firm's business ethics practices, including bribery, and fraud.	KLD
$Tax\ Disputes$	A discrete variable that indicates whether companies have recently been involved in major tax disputes involving Federal, state, local or	KLD
$Cash/StockSharing$	A discrete variable that indicates whether companies have a cash profit-sharing program through which it has recently made distributions to a significant proportion of its workforce. This variable also indicates whether companies encourage worker involvement via generous employee stock ownership plans (ESOPs) or employee stock purchase plans (ESPPs)	KLD
$Human\ Rights$	A discrete variable that is the net measure of positive features and negative features regarding human rights for a corporation. Positive features include quality labor rights, a strong relationship with indigenous peoples in foreign operations, and other human rights strengths. Negative features include human rights violations, including freedom of expression and censorship concerns, indigenous peoples relations concerns, labor rights concerns, operations in Sudan, Mexico, Burma, Northern Ireland and South Africa, and other human rights concerns.	KLD

Continued on next page...

... table A.1 continued

Variable	Description	Source
<i>Product Quality</i>	A discrete variable that is the net measure of positive features and negatives features regarding product category. Positive features include insuring health and demographic risk, responsible investment, strong privacy and data security, financial product safety, chemical safety, opportunities in nutrition and health, access to communications, access to capital, benefits to economically disadvantaged, R&D innovation, and other product strengths. Negative features include customer relations concerns, antitrust concerns, marketing-contracting concerns, product safety concerns, and other product concerns.	KLD
Panel D - Patent Variables		
<i>Patents_{i,t}</i>	The number of patents adjusted for truncation and propensity biases that firm <i>i</i> applied for in year <i>t</i>	NBER, KPSS, HPD
<i>PatentCites_{i,t}</i>	The number of adjusted patent citations for firm <i>i</i> in year <i>t</i>	NBER, KPSS, HPD
<i>Pat/R&D_{i,t}</i>	<i>Adjpatents_{i,t}</i> scaled by <i>R&D_{i,t-1}</i>	NBER, KPSS, HPD
<i>Top10_{i,t}</i>	The number of a firm <i>i</i> 's patents that rank in the top 10% of citations in year <i>t</i>	NBER, KPSS, HPD
<i>Pdiv_{i,t}</i>	The patent diversity of a firm <i>i</i> 's new patents applied for in year <i>t</i> . This is calculated as 1 minus the hirfindahl index across the 36 technology patent categories for firm <i>i</i> in year <i>t</i> .	NBER, KPSS, HPD
<i>Cdiv_{i,t}</i>	The diversity of citations received on firm <i>i</i> 's new patents applied for in year <i>t</i> . This is calculated as 1 minus the Hirfindahl index of a firm's citations across the 36 technology patent categories for firm <i>i</i> in year <i>t</i> .	NBER, KPSS, HPD
<i>ACdiv_{i,t}</i>	The diversity of adjusted citations received on firm <i>i</i> 's new patents applied for in year <i>t</i> . This is calculated as 1 minus the Hirfindahl index of a firm's adjusted citations across the 36 technology patent categories for firm <i>i</i> in year <i>t</i> . These citations are adjusted for citation propensities within a technology class-year.	NBER, KPSS, HPD
Panel E - Misstatement Variables		
<i>Misstatement</i>	A dummy variable takes value to be 1 if firm is during or at the conclusion of an investigation against a company, an auditor, or an officer for alleged accounting and/or auditing misconduct	AAER

Continued on next page...

... table A.1 continued

Variable	Description	Source
<i>WC Accruals</i>	$((\Delta\text{Current Assets} - \Delta\text{Cash and Short-term Investments}) - (\Delta\text{Current Liabilities} - \Delta\text{Debt in Current Liabilities} - \Delta\text{Taxes Payable})) / \text{Average total assets}$	Compustat
<i>RSST Accruals</i>	$(\Delta\text{WC} + \Delta\text{NCO} + \Delta\text{FIN}) / \text{Average total assets}$, where $\text{WC} = (\text{Current Assets} - \text{Cash and Short-term Investments}) / (\text{Current Liabilities} - \text{Debt in Current Liabilities})$; $\text{NCO} = (\text{Total Assets} - \text{Current Assets}) - \text{Investments and Advances}$; $\text{FIN} = (\text{Total Liabilities} - \text{Current Liabilities} - \text{Long-term Debt})$; $\text{FIN} = (\text{Short-term Investments} + \text{Long-term Investments}) - (\text{Long-term Debt} + \text{Debt in Current Liabilities} + \text{Preferred Stock})$	Compustat
<i>Change in receivables</i>	$\Delta\text{Accounts Receivable} / \text{Average total assets}$	Compustat
<i>Change in inventory</i>	$\Delta\text{Inventory} / \text{Average total assets}$	Compustat
<i>% Soft assets</i>	$(\text{Total Assets} - \text{PP\&E} - \text{Cash and Cash Equivalent}) / \text{Total Assets}$	Compustat
<i>Change in cash sales</i>	Percentage change in cash sales $(\text{Sales} - \Delta\text{Accounts Receivable})$	Compustat
<i>Change in cash margin</i>	Percentage change in cash margin, where cash margin is measured as: $1 - ((\text{Cost of Good Sold} - \Delta\text{Inventory} + \Delta\text{Accounts Payable}) / (\text{Sales} - \Delta\text{Accounts Receivable}))$	Compustat
<i>Change in ROA</i>	$(\text{Earnings}_t / \text{Average total assets}_t) - (\text{Earnings}_{(t-1)} / \text{Average total assets}_{(t-1)})$	Compustat
<i>Existence of Operating leases</i>	A dummy variable takes value to be 1 if future operating lease obligations are greater than zero	Compustat
<i>Actual issuance</i>	A dummy variable takes value to be 1 if the firm issued securities during year t (i.e., A dummy variable takes value to be 1 if "Sale of Common and Preferred Stock" > 0 or "Long-Term Debt - Issuance" > 0)	Compustat
<i>Abnormal change in employees</i>	Percentage change in the number of employees - percentage change in assets	Compustat
<i>Market-adjusted stock return</i>	Annual buy-and-hold return inclusive of delisting returns minus the annual buy-and-hold value-weighted market return	Compustat

Table A.2: Determinants of AshleyMadison Membership

In this table we report estimates for determinants of the number of active AshleyMadison (AM) accounts at the firm-level. We use Tobit specifications because the dependent variable, the natural logarithm of one plus the number of active AM accounts, is truncated at zero and continuous to the right of zero. Industry covariates are defined using four-digit SIC codes and geography covariates are defined at the zipcode level. Detailed variable definitions are provided in the appendix. All specifications have year fixed effects, specifications (2-6) include industry (three-digit SIC) fixed effects, and specifications (3-6) include EA fixed effects. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. We also report sigma and pseudo r-squared from the Tobit regressions. In unreported analyses we find qualitatively similar and statistically significant results using a linear probability model specification.

VARIABLES	(1) Active AM Accounts	(2) Active AM Accounts	(3) Active AM Accounts	(4) Active AM Accounts	(5) Active AM Accounts	(6) Active AM Accounts
Log Market Cap	0.214*** (8.60)	0.148*** (5.58)	0.122*** (39.68)	0.118*** (36.00)	0.121*** (35.65)	0.117*** (33.40)
Firm Age	0.003 (0.99)	0.003 (1.08)	0.005*** (6.53)	0.005*** (6.25)	0.004*** (6.07)	0.005*** (5.94)
Log # of Employee	0.306*** (13.66)	0.409*** (13.78)	0.420*** (89.94)	0.425*** (87.99)	0.420*** (88.13)	0.425*** (86.28)
Volatility-3 Factor adjusted	0.999 (0.30)	3.621 (1.22)	3.180*** (4.68)	3.008*** (4.15)	3.092*** (4.07)	2.915*** (3.73)
Population Density					0.024 (0.00)	1.965 (0.16)
Population					0.036*** (9.97)	0.037*** (9.85)
Median Population Age					-0.028*** (-41.44)	-0.028*** (-40.37)
Avg Income per Household					-4.300*** (-10.05)	-5.093*** (-11.57)
HHI (SIC4)				-0.044 (-0.91)		-0.046 (-0.91)
Market to Book (SIC4)				-0.002 (-0.38)		-0.002 (-0.35)
R&D intensity (SIC4)				0.659*** (5.13)		0.673*** (5.05)
Sales growth rate (SIC4)				0.003 (0.06)		0.002 (0.06)
sigma	1.503*** (46.06)	1.368*** (45.42)	1.314*** (179.15)	1.313*** (171.34)	1.314*** (168.38)	1.312*** (164.61)
Observations	28,374	28,374	27,824	27,754	27,792	27,722
Year FE	✓	✓	✓	✓	✓	✓
Industry FE		✓	✓	✓	✓	✓
E/A FE			✓	✓	✓	✓
Pseudo-R2	.12	.174	.198	.198	.198	.198

Table A.3: Abnormal AshleyMadison Membership and Corporate Outcomes

This table presents differences in means of key corporate outcome variables for firms with positive and negative abnormal AM membership (res). res is the residual from the following equation: $AM_{i,t} = a + b_1 Ln(Emp_{i,t}) + b_2 [Ln(Emp_{i,t})]^2 + b_3 [Ln(Emp_{i,t})]^3 + b_4 Ln(MktCap_{i,t}) + b_5 Ln(MktCap_{i,t})^2 + b_6 Ln(MktCap_{i,t})^3 + Year_t + EA_{i,t}$, where AM is the number of active AM accounts, Emp is the number of employees, $Year$ is a time fixed effect, and EA is a geography (Economic Area) fixed effect for firm i 's headquarters at time t . We examine the means of corporate outcome variables for sets of firms based on whether res is greater or less than 0. The corporate outcome variables are related to AAER misstatements (Panel A), KLD analyst ratings (Panel B), firm risk (Panel C), and corporate innovation (Panel D). Δ is the difference in means for the corporate outcome variables between the negative and positive res groups. All reported coefficients in panel A are multiplied by 100.

Panel A: AAER Misstatements							
Misstatement	Bribe	Fraud	Inflated	Fraud/Inflated	PFraud	Auditor	
res < 0	0.0057	0.182	0.255	0.380	0.068	0.079	
res > 0	0.0397	0.293	0.397	0.586	0.199	0.070	
Δ	-0.034**	-0.111*	-0.142**	-0.206***	-0.131***	0.00993	
t-stat	(-2.268)	(-1.898)	(-2.065)	(-2.447)	(-3.076)	(0.289)	
Panel B: KLD Ethics							
Bribery and Fraud	Tax Disputes	Hum Rights	Prod Qual	Profit Sharing			
res < 0	0.018	-0.021	-0.013	0.133			
res > 0	0.028	-0.039	-0.023	0.186			
Δ	-0.009***	0.018***	0.010**	-0.053***			
t-stat	(-2.813)	(4.001)	(1.993)	(-6.481)			
Panel C: Corporate Innovation							
Pat/R&D	Patent Cites	Patents	Top10 Citation	R&D/Sales	Pdiv	Cdiv	ACdiv
res < 0	0.047	0.031	0.003	1.391	0.025	0.026	0.026
res > 0	0.067	0.052	0.015	1.692	0.038	0.039	0.039
Δ	-0.004***	-0.021***	-0.012*	-0.301***	-0.013***	-0.013***	-0.013***
t-stat	(-3.448)	(-5.777)	(-1.689)	(-12.88)	(-6.083)	(-6.033)	(-6.096)
Panel D: Firm Risk							
Book Leverage	Market Leverage	Tobin's Q	Market to Book	Z-score	Volatility	Skewness	CDS Spread
res < 0	0.177	0.425	2.017	5.226	0.026	0.366	0.023
res > 0	0.186	0.413	2.068	5.491	0.024	0.358	0.021
Δ	-0.009***	0.0124	-0.052***	-0.264***	0.002***	0.008	0.003
t-stat	(-3.688)	(0.801)	(-2.380)	(-3.468)	(12.47)	(0.857)	(1.150)

Table A.4: AAER Misstatements and AshleyMadison Membership:

In this table we report marginal effects estimates for probit regressions of accounting misstatements on the number of active Adjusted AshleyMadison (AM) accounts (Natural log of number of Active AM Accounts minus natural log of number of employee). Data on misstatements from 2002-2014 come from the AAER dataset discussed in Dechow, Ge, Larson, and Sloan (2011). This dataset provides detailed information regarding misstatement investigations for public corporations. Specification 1 reports estimates for all types of misstatements in general, not distinguishing between misstatement type. Specification 2 reports estimates for bribery related investigations, specification 3 for corporate fraud, and specification 4 for inflation of earnings or assets. In specification 5 we combine fraud and inflation related misstatements. Specification 6 is related to personal fraud by company management (embezzlement, insider trading and alike). Specification 7 is for auditor's misstatements (related to problems with the audit itself). Our regressor of interest is the natural logarithm of one plus the number of active AM accounts for a given firm year. All specifications include year fixed effects, and all dependent variables are lagged by one year. All reported coefficients in specifications (1,2,4-7) are multiplied by 100, coefficients in specification (3) are multiplied by 10,000. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. Control variables are the same as in Table 5 and are omitted for brevity.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Misstatement	Bribe	Fraud	Inflated	Fraud_Inflated	PFraud	Audit	Misstatement
Adjusted Active AM Account	0.165*** (3.783)	0.019*** (5.869)	0.007*** (11.35)	0.129*** (3.882)	0.129*** (3.882)	0.046* (1.794)	0.0004 (1.441)	0.249 (1.80)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,838	2,744	3,540	5,837	5,837	3,540	5,837	22,557
Pseudo R2	.084	.213	.338	.072	.072	.149	.069	0.219

Table A.5: Corporate Ethics and AshleyMadison Membership

In this table we report OLS estimates for KLD ratings of firm behavior on the number of active AshleyMadison (AM) accounts. KLD ratings are annual company performance indicators with respect to meeting stakeholder needs regarding environmental, social, and governance factors. The indicators are developed by MSCI analysts who provide research for institutional investors. The KLD data are described in greater detail in section 2.2. As the dependent variable we use the number of positive ratings minus the number of negative ratings within a given KLD category. Our regressor of interest is the natural logarithm of one plus the number of active AM accounts for a given firm year. All regressors are lagged one year relative to our KLD measures. All other variables are defined in the appendix. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. Control variables are the same as in Table 6 and are omitted for brevity.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Adjusted Active AM Account	0.033*** (4.46)	0.020*** (2.76)	-0.017** (-2.44)	-0.014* (-1.89)	0.030*** (2.45)
Controls	✓	✓	✓	✓	✓
Observations	3,079	8,016	14,288	14,294	10,674
R-squared	0.24	0.21	0.15	0.14	0.24
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
EA FE	✓	✓	✓	✓	✓

Table A.6: Corporate Innovation and AshleyMadison Membership

In this table we report OLS estimates for the association between the number of active Adjusted AshleyMadison (AM) accounts (Natural log of number of Active AM Accounts minus natural log of number of employee) and firm-level innovation. We look at common measures of innovation using patent data from 2002-2005. Specifically, we look at truncation adjusted patents (column 1), log of adjusted patents (column 2), patents scaled by R&D expenses (column 3), R&D expenses scaled by lagged assets for 2002-2005 (column 4), patent diversity (column 5), citations per patent (column 6) and R&D expenses scaled by lagged assets for 2002-2014 (column 7). Our regressor of interest is the natural logarithm of one plus the number of active AM accounts for a given firm year. Our sample conditions on firms that have at least one patent from 2002-2005. This is to mitigate inferences being contaminated by systematic differences between patenting and non-patenting firms. All specifications include year, industry (3 digit sic code), and EA fixed effects. All regressors are lagged one year relative to our innovation measures. All variables are defined in the appendix and within the text. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. Control variables are the same as in Table 7 and are omitted for brevity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Patent	R&D	R&D/Sales	Patents/R&D	Citations	Citations/R&D	Pdiv	Cdiv
Adjusted Active AM Account	0.439*** (37.62)	0.219** (2.40)	0.022** (2.45)	0.018*** (17.45)	6.659*** (38.45)	0.069*** (15.88)	0.109*** (25.18)	0.105*** (23.56)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18,708	18,708	18,708	18,708	18,708	18,708	18,708	18,708
Pseudo R-squared	0.292	0.301	0.800	0.496	0.202	0.389	0.373	0.350

Table A.7: AshleyMadison Membership and the Choice of Internal vs. External CEO

In this table we report the marginal effects estimates from a probit regression of choosing an internal CEO (1) vs. external CEO (0) on the number of active Adjusted AshleyMadison (AM) accounts (Natural log of number of Active AM Accounts minus natural log of number of employee). The data on CEOs come from Boardex for 2003-2014. We define a CEO as internal if he/she was employed at a given company for at least one full year before being appointed as CEO. Our regressor of interest is the natural logarithm of one plus the number of active AM accounts for a given firm year. Specifications 2-6 include year fixed effects, column 5 includes industry (2 digit sic code) fixed effects, and column 6 includes industry and EA fixed effects. All regressors are lagged one year relative to our CEO appointment variables. All variables are defined in the appendix and within the text. The t-statistics, calculated from standard errors clustered at the firm level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

VARIABLES	(1) isINCEO	(2) isINCEO	(3) isINCEO	(4) isINCEO
Active Adjusted AM Accounts	0.088*** (12.00)	0.087*** (10.18)	0.179*** (12.99)	0.563*** (11.30)
Controls	✓	✓	✓	✓
Observations	991	991	886	727
Pseudo-R2	.068	.077	.171	.499
Year FE	✓	✓	✓	✓
2-digit SIC FE			✓	✓
EA FE				✓

Table A.8: AM Membership and going public.

All variables are defined in the appendix and within the text. The t-statistics, calculated from standard errors clustered at the industry level, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively. Panel C reports matching sample estimates for main innovation intensity and quality variables.

VARIABLES	Panel A: Patent and R&D								
	(1) Active AM	(2) Active AM	(3) Active AM	(4) Active AM	(5) Active AM	(6) Active AM	(7) Active AM	(8) Active AM	(9) Active AM
Post	0.114*** (8.98)	0.103*** (8.066)	0.058*** (6.033)	0.065*** (5.93)	0.058*** (5.06)	0.059*** (5.371)	0.051*** (3.731)	0.088*** (8.184)	0.087*** (7.73)
Log # of Employee			0.240*** (14.78)	0.239*** (14.91)	0.237*** (14.32)	0.241*** (14.44)	0.241*** (14.46)	0.074*** (3.511)	0.074*** (3.501)
IPO year				-0.036* (-1.970)	-0.033* (-1.873)	-0.033* (-1.927)	-0.035* (-2.034)	-0.051*** (-6.060)	-0.051*** (-6.137)
VC backed						0.043*** (13.83)	0.030*** (7.249)		-0.001 (-0.460)
VC backed × Post							0.040** (2.742)		0.003 (0.443)
Constant	0.123*** (34.45)	0.127*** (27.56)	0.007 (1.097)	0.007 (1.168)	0.001 (0.113)	-0.011* (-2.095)	-0.007 (-1.198)	0.099*** (8.176)	0.100*** (7.99)
Industry FE		✓	✓	✓	✓	✓	✓		
EA FE					✓	✓	✓		
Firm FE								✓	✓
Observations	26,364	26,364	24,910	24,910	24,910	24,910	24,910	24,910	24,910
R-squared	0.013	0.181	0.275	0.275	0.337	0.337	0.338	0.917	0.917

Table A.9: AshleyMadison Membership and Portfolio Returns

In this table we report the portfolio return based on the number of active AshleyMadison (AM) accounts from 2002-2014. We form long equal-weighted portfolios of all firms with AM and short equal-weighted portfolio of all firms without AM accounts. We form the portfolio in January based on previous year AM accounts. We then repeat the analysis with more restricted samples of AM accounts. 4 accounts represents the 90 percentile and 9 accounts the 95 percentile. The t-statistics, calculated from robust standard errors, are reported in parentheses below coefficient estimates. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

	AM(Yes) - AM(No)	AM(>=2) - AM(0)	AM(>=4)-AM(0)	AM(>=9)-AM(0)
Raw Return	3.05%*** (2.834)	3.42%*** (2.802)	3.39%*** (2.417)	3.47%*** (2.093)
CAPM - α	3.11%*** (2.727)	3.53%*** (2.727)	3.67%*** (2.523)	4.12%*** (2.470)
R2	0.001	0.002	0.014	0.052
Fama-French 3 factor - α	3.34%*** (2.985)	3.78%*** (2.998)	3.88%*** (2.688)	4.36%*** (2.630)
R2	0.042	0.043	0.034	0.080
Fama-French-Carhart 4 factor - α	3.21%*** (2.747)	3.61%*** (2.742)	3.67%*** (2.418)	4.04%*** (2.350)
R2	0.047	0.050	0.042	0.090
N	156	156	156	156

Table A.10: AshleyMadison Membership and Portfolio Returns

In this table we report for each size quartile Fama-French-Carhart four factor annualized α of long-short portfolios sorted on size and Ashley-Madison membership. For each size quartile long portfolio is including all firms with active AM account in year t , and short portfolio includes firms without AM accounts. We form the portfolio in January based on previous year AM accounts. The t-statistics, calculated from robust standard errors, are reported in parentheses below coefficient estimates. We report both equally and value-weighted portfolios results based on 2002-2014 (156 monthly observations). Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

Value Weighted portfolios	1 (Small)	2	3	4(Large)
Fama-French-Carhart-4-factor α	0.0500*** (3.23)	0.0497*** (3.71)	0.0360*** (3.55)	-0.0044 (-0.52)
Equally weighted portfolios	1 (Small)	2	3	4(Large)
Fama-French-Carhart-4-factor α	0.0491*** (3.44)	0.0576*** (4.08)	0.0399*** (3.87)	0.0160** (2.23)

Table A.11: Fama-MacBeth Regressions of Monthly Returns on AM Active Measure, R&D, and Ability

This table presents monthly Fama-MacBeth (1973) regressions of returns on AM Active Measure, R&D and Ability. AM Rank is equal to 1 if AM_active measure in a given year is positive, and zero otherwise. The R&D (Ability estimate) used in the regression is the R&D (Ability estimate) from the fiscal year ending in calendar year $t-1$ from July to December and calendar year $t-2$ from January to June (as in Fama and French (1993)). Ability is computed as described in Cohen, Diether, and Malloy (2013). High Ability (Low Ability) equals one if a stock is in the top (bottom) quintile for a given month. High R&D (Low R&D) equals one for a stock if its ability estimate is greater than the 70th (not greater than the 30th) percentile in a given month. Zero R&D equals one if R&D = 0. $\log(\text{ME})$ is the log of month $t-1$ market-cap, and $\log(\text{B}/\text{M})$ is log book to market defined and lagged as in Fama and French (1993). $r_{12,2}$ is the return from month $t12$ to month $t2$. r_{-1} is the one month lagged return. turnover is average daily share turnover ($\times 100$) over the past year. σ is the standard deviation of daily returns over the past year. The regressions only include stocks with lagged price greater than 5. The sample period is January 2002 to December 2014. T-statistics are in parenthesis. Statistical significance (two-sided) at the 1% 5%, and 10% level is denoted by *, **, and ***, respectively.

VARIABLES	(1) Return	(2) Return	(3) Return	(4) Return	(5) Return
AM Rank	0.002*** (3.565)		0.002*** (3.679)	0.002*** (3.337)	0.002*** (3.339)
Active AM Account		0.001** (2.438)			
AM Rank * High Ability			-0.001 (-0.445)	-0.002 (-0.886)	-0.002 (-0.637)
AM Rank * Low Ability			-0.001 (-0.688)	-0.001 (-0.502)	-0.001 (-0.256)
AM Rank * High R&D				0.007** (2.286)	0.007** (2.347)
AM Rank * Low R&D				0.004 (1.547)	0.004 (1.498)
AM Rank * Zero R&D				0.003 (1.034)	0.003 (0.923)
AM Rank * High Ability * High R&D					-0.004 (-0.390)
AM Rank * Low Ability * High R&D					0.005 (0.668)
High R&D * High Ability	0.002 (0.373)	0.002 (0.401)	0.002 (0.466)	0.003 (0.646)	-0.004 (-0.390)
High R&D * Low Ability	-0.007 (-1.633)	-0.007 (-1.635)	-0.007* (-1.746)	-0.007* (-1.736)	0.005 (0.668)
High Ability	0.001 (1.380)	0.001 (1.054)	0.002 (0.962)	0.005 (1.361)	0.005 (1.168)
Low Ability	0.001 (1.164)	0.001 (0.921)	0.003 (1.051)	0.004 (1.074)	0.003 (0.859)
Zero R&D	-0.004 (-1.520)	-0.002 (-0.731)	-0.003 (-1.042)	-0.018* (-1.714)	-0.018* (-1.681)
Low R&D	-0.003 (-1.184)	-0.001 (-0.377)	-0.002 (-0.731)	-0.019* (-1.853)	-0.019* (-1.843)
High R&D	-0.005 (-1.497)	-0.002 (-0.854)	-0.004 (-1.083)	-0.024** (-2.358)	-0.024** (-2.392)
Log Market Cap	-0.001* (-1.808)	-0.001 (-1.087)	-0.001 (-1.236)	-0.004** (-2.236)	-0.004** (-2.243)
Log B/M	-0.0008 (-1.312)	-0.0007 (-1.282)	-0.0008 (-1.315)	-0.0008 (-1.292)	-0.0008 (-1.303)
$r_{-12,-2}$	0.001 (0.600)	0.001 (0.612)	0.001 (0.602)	0.001 (0.609)	0.001 (0.616)
r_{-1}	0.001 (0.600)	0.001 (0.612)	0.001 (0.602)	0.001 (0.609)	0.001 (0.616)
Turnover	-0.002* (-1.721)	-0.002 (-1.621)	-0.002* (-1.732)	-0.002* (-1.711)	-0.002* (-1.712)
σ	-0.095** (-2.381)	-0.096** (-2.413)	-0.095** (-2.371)	-0.095** (-2.381)	-0.095** (-2.370)
Constant	0.038** (2.032)	0.026 (1.535)	0.033 (1.442)	0.101** (2.346)	0.102** (2.351)
Observations	411,801	411,801	411,801	411,801	411,801
Number of groups	156	156	156	156	156