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Do Good Times Breed Cheats?

Prosperous times have immediate and lasting implications for CEO misconduct

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Abstract

We examine whether prosperous economic times have both immediate and lasting implications for corporate misconduct among CEOs. Drawing on research suggesting that prosperous times are associated with excessive risk-taking, overconfidence, and more opportunities to cheat, we first propose that CEOs will be more likely to engage in corporate misconduct during good economic times. Next, we propose that CEOs who begin their careers in prosperous times will be more likely to engage in self-serving corporate misconduct later in their careers. We tested these hypotheses by assembling a large dataset of American CEOs and following their stock option reporting patterns between 1996 and 2005. We found that in good economic times, CEOs were more likely to backdate their stock options grants. Moreover, CEOs who began their careers in prosperous times were more likely to backdate stock option grants later in their careers. These findings suggest that the state of the economy can influence current ethical behavior and leave a lasting imprint on the moral proclivities of new workforce entrants.

Keywords: ethics, CEO misconduct, backdating, macroeconomy, recessions
“Never before have so many unskilled twenty-four-year-olds made so much money in so little time as we did this decade in New York and London. There has never before been such a fantastic exception to the rule of the marketplace that one takes out no more than one puts in.”

-Michael Lewis (1989), *Liar’s Poker*

When Michael Lewis and his cohort entered Wall Street in the mid-1980s, signs of American prosperity were seemingly everywhere. Extravagant demonstrations of wealth were visible and common, from expensive new china in the White House to glamorous birthday parties for celebrity CEOs (Mills, 1991). Madonna’s “Material Girl” cracked the Billboard Top 5 and Wall Street titans such as Ivan Boesky and Michael Milken became public celebrities who earned outsized salaries and spent lavishly. Like many prosperous periods, the 1980s were also plagued by ethical scandals (e.g., Galbraith, 1954; Kindleberger and Aliber, 2005; Akerlof and Shiller, 2009). By the end of the decade, over half the Savings and Loans Banks had failed and over 1,000 executives, many from well-known banks, faced federal indictments (Eisenger, 2014). Five United States senators became entangled in a corruption scandal and both Boesky and Milken were imprisoned for securities fraud.

In this paper, we examine whether such prosperous times have both immediate and lasting implications for corporate misconduct among CEOs. Drawing on work showing that prosperous times are associated with risk-taking, overconfidence, greater opportunities to cheat and lax oversight, we argue that CEOs will be more likely to cheat in prosperous relative to lean economic times. We also argue that economic conditions at the beginning of a CEO’s career will affect the likelihood of engaging in ethically-suspect practices later on. Specifically, we propose that CEOs who enter the workforce during prosperous times will be more likely to use unethical means for personal gain later in their careers than CEOs who begin their careers in leaner economic times. Like other scholars, we define corporate misconduct as behavior that is illegal, violates collectively agreed upon norms, or directly harms employees or shareholders (e.g., Jones, 1991; Gino & Pierce, 2009).

**Economic Conditions and Unethical Behavior**

At first glance, it seems likely that recessions might engender rather than temper corporate misconduct. During recessions, resources shrink and needs swell. When resources are scarce, engaging in unethical behavior may be more economically valuable and materially tempting.
Consistent with this reasoning, recent work has shown that financial deprivation can loosen moral standards and increase the likelihood of engaging in immoral conduct (Sharma et al, 2014). Similarly, other work suggests that when organizations are under strain, corporate leaders are driven to alleviate this pressure through any means necessary, including engaging in illegal behavior (Staw and Szwajkowski, 1975; Finney and Lesieur, 1982; Vaughn, 1999). Reasoning from prospect theory also appears to suggest that recessions might cultivate misconduct. During downturns, corporate leaders are more likely to face losses and may take excessive risks to recover these deficits (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). If such risks include pushing ethical boundaries, then unethical behavior may thrive when the economy flounders.

In this paper, we make the opposite prediction, namely that workplace misconduct among CEOs will shrink during downturns and swell during booms. We base this prediction on several lines of reasoning. The first is opportunity. During booms, credit is more accessible and capital is plentiful, making it easier to attract investors and fund ethically dubious ventures (Noe and Robello, 1994; Ruckes, 2004; Kindleberger & Aliber, 2005; Akerlof and Shiller, 2009). In addition, as financial bubbles swell and profits flourish, new investors often flood financial markets. These new investors tend to be less sophisticated, making it easier for swindlers to prosper and suspect practices to go undetected (Lux, 1995; Kindleberger & Aliber, 2005; Akerlof and Shiller, 2009). Moreover, outsiders tend to be less vigilant detectives of unethical behavior during booms (Povel, Singh, & Winton, 2007; Philippon, 2006). When people are making money, they are less likely to question suspicious practices and police greedy executives. Indeed, people are more likely to cheat a little bit when they believe their transgressions will avert detection (Gino, Ayal, & Ariely, 2009; Mazar, Amir, & Ariely, 2008) and they seem to be more likely avert detection when things are going well. Consequently, scholars have suggested that managers and firms are more incentivized to commit fraud during booms, in part because the payoffs of fraud are particularly high at the same time that monitoring is relatively low (Povel, Singh, & Winton, 2007). Thus, the opportunity to engage in ethically suspect practices is likely to be higher in good economic times.

In addition to opportunity, prosperous times are also likely to engender ethical missteps through psychological mechanisms such as overconfidence and increased comfort with risk (Coates
and Herbert, 2008; Galbraith, 1954; Kindleberger and Aliber, 2005; Shiller, 2005). During booms, investments are more likely to yield positive returns and risk-taking tends to become increasingly extreme. For instance, one study of London stock traders showed that when the market was rising, testosterone increased, risk appetites swelled, and traders made increasingly larger bets (Coates and Herbert, 2008). Another study found that when financial professionals were primed with signals of prosperity, they took greater risks (Cohn et al, 2015). Indeed, booms have been described as periods of “irrational exuberance” (Greenspan, 1996), “mania” (Kindleberger and Aliber, 2005) and “speculative make-believe” (Galbraith, 1954), all of which reflect unbridled optimism and a greater penchant for risk-taking.

This mentality can direct attention towards possible rewards from unethical behavior and away from potential negative consequences (Thaler and Johnson, 1990; Gino and Margolis, 2011; Coates, 2012). For instance, one study found that overconfident executives were more likely to commit reporting fraud in part because they were over-optimistic about future returns (Schrand and Zechman, 2012). When the gains did not materialize they were more likely to fudge accounting figures to cover these blunders. Moreover, overconfidence and its accompanying aura of invincibility may lead people to underestimate the likelihood that their misdeeds will be detected (Gino and Margolis, 2011). Indeed, firms are more likely to commit fraud when they exceed earnings aspirations and expectations, in part because success provokes a sense of invincibility (Mishina, Dykes, Block, and Pollock, 2010).

On the surface, these findings appear at odds with the predictions from prospect theory noted earlier. While prospect theory seems to predict that executives may be particularly risk seeking during busts to recoup losses, empirical examinations show that risk-seeking actually rises during booms (Barberis, Huang, and Santos, 2001; Acharya & Naqvi, 2012; Cohn et al., 2015). For instance, many scholars have attributed the recent subprime mortgage crisis to excessive risk taking among financial firms (Shiller, 2012). Other recent work has shown that when financial professionals are primed to think about prosperous times, they select riskier investments (Cohn, et al, 2015). One way to reconcile these findings with prospect theory is through aspirations and expectations (Harris and Bromley, 2007; Greve, Palmer, and Pozner, 2010). Leaders and organizations tend to assess their outcomes
against the performance of salient others as well against their own past performance (Cyert & March, 1963; Harris and Bromiley, 2007). When a firm exceeds its past performance or when other salient firms are doing well, aspirations and expectations soar (Greve, Palmer, and Pozner, 2010; Harris and Bromiley, 2007; Mishina, Dykes, Block, and Pollock, 2010). In good times, firms are both more likely to exceed past performance and watch comparisons firms excel. As a result, expectations and aspirations will likely swell and corporate leaders may be willing to do whatever it takes to meet rising expectations (Greve, Palmer, and Pozner, 2010; Mishina, Dykes, Block, and Pollock, 2010). Indeed, similar logic has been used to account for why CEOs are more likely to engage in misconduct when their firms are doing particularly well (Mishina, Dykes, Block, and Pollock, 2010), why investors are more risk seeking in good economic times (e.g. Barberis, Huang, and Santos, 2001; Cohn et al., 2015), and why signals of abundance increase the prevalence of cheating (Gino and Pierce, 2009).

Consistent with the idea that booms cultivate overconfidence, risk taking, and ethical missteps, economic booms are often associated with major corporate ethics scandals (Galbraith, 1954; Kindleberger and Aliber, 2005; Povel, Singh, and Winton, 2007). The boom of the 1980s was followed by the Savings and Loans Scandal and the widespread indictment of bank executives. The internet bubble of the late 1990s was followed by revelations of financial improprieties and fraudulent accounting at major corporations such as Enron, WorldCom, and Tyco (Kindleberger and Aliber, 2005; Povel, Singh, and Winton, 2007; Akerlof and Shiller, 2009). Each economic boom has a cast of corporate villains, from Ivan Boesky and Michael Milliken in the boom of the 1980s to Dennis Kozlowski and Kenneth Lay in the economic surge of the late 1990s and Dick Fuld and Bernie Madoff in the early 2000s.

While booms have been described as periods of overconfidence, excessive optimism, and an increased appetite for risk, recessions are characterized by uncertainty, caution, and fear (Galbraith, 1954; Kindleberger and Aliber, 2005; Akerlof and Shiller, 2009; Bianchi, 2016). When resources are scarce and the economy is floundering, people hold others to higher moral standards and are more vigilant detectives of immoral behavior, in part because of increased vulnerability to unethical acts (Povel, Singh, and Winton, 2007; Pitesa and Thau, 2014). In addition, oversight and regulation tend to
flourish during downturns in part to mitigate uncertainty and vulnerability (Galbraith, 1954; Kindleberger and Aliber, 2005; Shiller, 2005). Indeed, as Galbraith (1954) wrote, “[during recessions] money is watched with a narrow, suspicious eye…Audits are penetrating and meticulous. Commercial morality is enormously improved” (p. 134). In sum, during challenging economic times, people are both more fearful, risk-averse, and wary of fraud-minded others (Kindleberger and Aliber, 2005; Povel, Singh, and Winton, 2007). As such, we predicted that during such times, corporate leaders would be less likely to engage in corporate misconduct.

_Hypothesis 1: CEOs will be less likely to utilize unethical business practices during bad economic times and more likely to utilize such practices during good economic times._

**The Imprint of Early Work Experiences**

Our second prediction is that entering the workforce during an economic boom will have lasting implications for how likely new workers are to engage in corporate misconduct later in their careers. Early career experiences can leave an enduring mark on the mental models and approaches to work that executives carry with them throughout their adult lives (Higgins, 2005; Malmendier and Nagel, 2011; Malmendier, Tate, and Yan, 2011; Schoar and Zuo, 2012; Bianchi, 2013; Marquis and Tilcsik, 2013; Bianchi, 2014). Early in their careers, people are particularly sensitive to the socializing influences of their surroundings and tend to develop routines, norms, and practices that are adaptive to these early career environments (Higgins, 2005; Marquis and Tilcsik, 2013).

Economic conditions during this sensitive period can leave a particularly strong mark on the behavior and management styles of CEOs (Malmendier, Tate, and Yan, 2011; Schoar and Zuo, 2012). For instance, CEOs who start their working lives in economic booms tend to favor riskier financial strategies, such as greater leveraging, higher overhead costs, or minimal diversification (Malmendier, Tate, and Yan, 2011; Schoar and Zuo, 2012). Those who come of age in downturns, however, tend to be more deliberate and risk averse, reflecting the more cautious mood of their early working lives. Moreover, CEOs who begin their careers amidst economic prosperity tend to exhibit greater narcissism later on, presumably reflecting the greater individualism and excessive confidence of the period in which they came of age (Bianchi, 2014).
Building on this work, we expected that CEOs who began their working lives during an economic boom would be more likely to adopt an ethically lax approach to work. These new workers have few existing templates for how work is done, which rules are followed, and which shortcuts are customary. Thus, they are particularly apt to look to others to determine whether it is acceptable to double bill a client or inflate an expense report. Indeed, past work has shown that new workers are particularly likely to be become acclimated to morally questionable business practices often without explicitly recognizing the ethical implications of their behavior (Ashforth and Anand, 2003). Moreover, as novices trying to ascend the organizational hierarchy, new workers are likely to feel particularly strong pressure to adopt existing norms, even if they do recognize the immorality of a practice. For instance, one workplace ethics survey found that employees who were early in their careers and relatively new to their organizations were twice as likely to feel pressure to compromise their ethical standards compared to older, more tenured adults (Ethics Resource Center, 2003).

For CEOs who begin their careers in prosperous times, taking shortcuts and pushing ethical boundaries may become the template for how things are done and what it takes to succeed and survive. Unethical behavior is a domain in which people are particularly apt to look to others when assessing what is normative and acceptable (Cialdini, 1984; Cialdini and Trost, 1998; Moore and Gino, 2013). For instance, people are more likely to cheat on their tax returns when they believe others are cheating (Wenzel, 2005) and more likely to litter when they see another person litter first (Cialdini, Reno and Kallgren, 1990). Once established, these routines often become habits that endure across time and organizations (Higgins, 2005). Thus, we expect that CEOs who enter the workforce in prosperous times will be more likely to employ unethical tactics when the opportunity arises.

**Hypothesis 2:** CEOs who begin their careers in prosperous times will be more likely to utilize unethical business practices than CEOs who begin their careers in more lean economic times.

These hypotheses seek to make two primary contributions to scholarship on misconduct among corporate elites. First, while past research has considered contextual antecedents of CEO misconduct, much of this work has focused on proximal variables within the organization. For instance, studies have found that CEOs are more likely to manipulate earnings (Bergstresser and Philippon, 2006) or commit securities fraud (Denis, Hanouna, and Sarin, 2006) if their compensation
is strongly tied to company performance. Other work has linked corporate misconduct to governance practices, such as the number of outside representatives on the board (e.g., Beasley, 1996). We seek to build on this work by considering whether strong situational forces outside the organization can similarly influence the likelihood of cheating. In doing so, this work highlights the role of broader macro-environmental events in shaping the moral behavior of CEOs.

Our inquiry also suggests that strong experiences at a formative stage of life can have lasting implications for ethical behavior later on. While organizational scholars have documented the costs and consequences of corporate misconduct (e.g., Greve, Palmer, & Pozner, 2008; Pfarrer, Decelles, Smith, and Taylor, 2008), relatively little is known about which CEOs are more likely to cheat. Past work has looked to relatively stable traits such as narcissism (Blickle, Schlegel, Fassbender, and Klein, 2006; Watts et al., 2013) or intelligence (Subrahmanyam, 2005) to predict which CEOs are more likely to engage in misconduct. The present work explores whether experiences at a formative stage of life can have lasting implications for how likely a CEO is to cheat at work later on.

METHODS

We tested our hypotheses by constructing a large dataset of CEOs who ran publically traded companies in the United States between 1996 and 2005. For each CEO, we tracked his stock option reporting patterns over a ten year period. We gauged corporate misconduct by examining the likelihood that each stock option grant awarded during this time was backdated. Backdating stock option grants was a fairly common and unscrupulous practice in the late 1990s and early 2000s (e.g., Lie, 2005; Carow, Heron, Lie and Neal, 2009). In a typical backdating event, a CEO would receive a stock option grant on one date but report that these options were assigned at an earlier date when the stock price was lower. This enabled him to realize greater gains than if he accurately reported the date of the award. For instance, a CEO who was issued stock options on a day when his company’s stock price was $100 could report that he actually received the options one week earlier when the stock price was $80. In doing so, he would receive an additional $20 per share gain when he exercised the options and sold the stock.

In the late 1990s, executives were required to report option awards to the SEC within one month and one week of the date the options were issued. This allowed considerable flexibility in
reporting the award date. This means that if the stock price on the day of the grant award was higher than the price in preceding or subsequent days, a CEO could simply report that the grant was awarded on a more favorable date (Lie, 2005). We focused on CEOs because data for these executives is relatively complete and accessible due to disclosure requirements. Moreover, reporting the date of a grant assignment to the Security and Exchange Commission (SEC) is often governed within the executive suite. Consequently, CEOs have more control over whether their stock options are backdated compared to other executives or directors (Wiersema and Zhang, 2013).

Backdating is typically illegal as well as highly unethical (Narayanan, Schipani, and Seyhun, 2007; Carow, Heron, Lie and Neal, 2009; Bebchuk, Grinstein, and Peyer, 2010; Wiersema and Zhang, 2013).¹ It requires lying about the date a grant was received and necessitates intentionally falsifying financial documents that are submitted to the SEC (e.g., Lie, 2005). Moreover, the additional gains received by a backdating executive come at the cost of company profits and shareholder returns (Narayanan, Schipani, and Seyhun, 2007). Following public exposure of backdating, many companies were forced to restate earnings reports and pay considerable fines. Many individual executives were forced to surrender ill-gotten gains, pay substantial civil penalties, and even relinquish their jobs (Wiersema and Zhang, 2013).

This practice began receiving considerable public attention following the publication of a Wall Street Journal front page story in March, 2006 (Forelle and Bandler, 2006), which chronicled the suspiciously fortuitous timing of stock awards at six large companies. In one company, a CEO received six separate stock option grants shortly before a sharp rise in the stock price. The estimated odds of this happening simply by luck were one in 300 billion. Academic research also confirmed that executives received stock options on favorable dates far more often than chance alone would predict (Heron and Lie, 2007; Lie, 2005; Yermack, 1997; Narayanan and Seyhun, 2008). One paper estimated that 29% of publically traded companies were engaged in backdating at some point (Heron and Lie, 2007).

¹ Backdating stock options can be legal if the following conditions are met: 1) the firm counts the additional gains received by backdating as a compensation expense and 2) the firm discloses this practice to the SEC and to shareholders in a timely manner (Wiersema and Zhang, 2013). However, if individuals or firms fulfill these requirements, there are no benefits from backdating. If properly reported, the additional income would be treated as taxable compensation for the individual and firms could record the additional gains as expenses reducing their tax liabilities. Consequently, very few people legally reported reissuing stock dates.
Following regulatory changes, the rate of unusually lucky award dates dropped considerably (Heron and Lie, 2009). This suggests that executives were not simply talented predictors of future stock gains. Rather, many were manipulating the date of their awards to realize greater profits (Heron and Lie, 2009).

Backdating provides several advantages for testing our hypotheses compared to other commonly used metrics of corporate misconduct such as earnings restatements or shareholder lawsuits. The first is detection. Only some cases of executive misconduct are actually detected and it is unclear whether such cases are representative of overall misconduct. Earnings restatements and shareholder lawsuits both rely on either detection or admission of misconduct. Backdating does not. As such, it is likely to capture a more comprehensive and representative sample of unethical behavior among CEOs.

A second advantage of backdating is that it can be linked directly to the CEO. CEOs have considerable control over whether their stock options are backdated (Lie, 2005; Bebchuk, Grinstein, and Peyer, 2010; Wiersema and Zhang, 2013). Other commonly used metrics of corporate misconduct, such as earnings restatements or shareholder lawsuits, can result from fraud or negligence by other members of the organization (Srinivasan, 2005). Indeed, one analysis found that CFOs not CEOs were most likely to be terminated following a major earnings restatement (Hennes, Leone, and Miller, 2008). Given that our second hypothesis focused on how individual career experiences influence later ethical behavior, we wanted to ensure that such behaviors were clearly under the CEO’s control.

**Sample**

We began by identifying 2,139 Chief Executive Officers of publically traded companies in the United States between 1996 and 2005 who received stock options from their company and were also covered in the BoardEx dataset. This initial sample was drawn from Thomson Reuters Insider Filings database and executives were matched by name to BoardEx. Thomson Reuters includes detailed reports from Table 2 of Form 144 submitted to the SEC indicating the date, price, and

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2 1996 was the first year Thomson Reuters collected reliable data on stock option grants. After the exposure of the practice, the rate of suspiciously lucky grants dropped to nearly zero (Heron and Lie, 2009).
number of options assigned to executives in each firm. This information enabled us to reliably estimate whether a stock option grant was likely backdated. BoardEx provides educational history for each executive, including each university attended, degrees received, and years of graduation. This information allowed us to gauge the economic conditions at the time each executive entered the job market. This data was supplemented with firm level data for each company from Compustat and stock price data collected from the Center for Research in Securities Prices (CRSP).

We first coded whether a CEO received his or her highest degree from a school in the United States. We only included CEOs who graduated from schools in the United States in order to have comparable workforce entry economic measures across CEOs. We manually verified the location of each university in our sample and successfully identified locations for 580 institutions. Of these, 510 (87.3%) were universities located only in the United States and 39 were universities located outside the United States. For the remaining 31 schools, we either found: 1) matching institutions both inside and outside the U.S. (for example, there is a “St. John’s University” both in York, United Kingdom and in Long Island, New York) or 2) no matching name anywhere.

We then identified the year each executive earned his or her highest degree. We did not include graduating from professional courses because executives are likely to have already been employed when enrolled in these programs (e.g., Executive MBA, supplementary professional courses etc.). Finally, we restricted our sample to executives who earned their degrees at or before age 30. Those who earned a degree after age 30 were likely to have had a substantial amount of work experience before returning to school and an additional degree at this stage of life is not likely to mark a meaningful career beginning (Bianchi, 2013). However, including people who earned their degrees after age 30 does not substantially change our results.

Our final sample consisted of 2,012 CEOs who attained their highest degree from U.S. universities, served as CEOs of a publically-traded company between 1996 and 2005, and received non-scheduled stock option grants. As shown in Figure 1, CEOs in this sample earned their degrees between 1948 and 1997. Most of the CEOs in our sample were born in the 1940s (N = 863) or the 1950s (N = 675), with the rest being born in the 1920s (N = 21), 1930s (N = 258), 1960s (N = 191) or 1970s (N = 4). On average, these CEOs received their highest degree at age 23.2 (SD = 2.47), and
more than half (58.4%) did not obtain advanced degrees after college. The vast majority were male (97%).

Backdating. An option grant was considered backdated if it was awarded on an extremely lucky date (Lie, 2005; Yermack, 1997). To gauge extreme luck, we first established a benchmark for what was likely to be a suspiciously lucky grant (Bizjak, Lemon and Whitbey, 2009; Heron and Lie, 2007). To do so, we simulated 100,000 randomly assigned “grants.” We calculated the simple mean and standard deviation of the return for each grant $i$ over the possible reporting window $[r_{it} = \frac{(p_{it} - \mu_{t+20})}{\mu_{t+20}}], \sigma_{it} = \sqrt{E[(p_{it} - \mu_{t+20})^2]}$. As expected, the simulated grants had an average return $r_{it} = 0$, since the average grant $i$ was given at a price that was on average $\mu_{t+20}$ (Heron and Lie, 2007; Bizjak, Lemon and Whitbey, 2009). The variance produced by this procedure was used to assess suspiciously well-timed grants. A grant was considered legitimate if it fell within the 95% confidence intervals for random grants assigned to the firm. A grant was considered suspiciously lucky and tagged as likely backdated if it fell outside the 95% confidence interval of our simulation and on the tail representing the lowest rather than the highest price.

We illustrate this identification strategy in Figure 2 using a grant reported by Gregory Reyes, the CEO of Broadcom in 2000. Based on the date these options were reported to the SEC, Reyes could have received the stock any time between April 26, 2000 and June 7, 2000. During this time, Broadcom’s stock fluctuated substantially, ranging from a high of $182 in late April to a low of $119 in late May. Our identification strategy computed the mean price of a theoretical, honest grant and created a 95% confidence interval for a truly random stock grant. Based on this strategy, grants would be tagged as suspiciously lucky if they were received on May 23rd or May 24th, the two days during the reporting window in which the stock price was unusually low.
Of course, there are times when executives are simply extremely lucky. Indeed, even if no grants were backdated, 2.5% of the grants should be categorized as very lucky simply by chance. However, nearly 15% of the grants in our sample were very lucky, a level far higher than chance alone would predict. Moreover, while our procedure captured some luck, this should only introduce noise to our models rather than drive any observed effects. Such noise should work against finding support for our predictions.

**Independent Variables**

*Current economic conditions.* Current economic conditions were gauged using the seasonally-adjusted monthly unemployment rate. The unemployment rate has several advantages over other measures of economic health. For one, it is more closely tied with perceptions of the economy than any other commonly used metric (Bianchi, 2016). Moreover, unlike other metrics such as GDP, stock market performance, or median income which tend to go up steadily over time, the unemployment rate does not typically show a strong upward or downward trend over long periods of time. This better enabled us to examine the effect of economic conditions apart from other time trends. For these reasons, the unemployment rate is the metric most commonly used to capture the effect of economic conditions on attitudes and behaviors (e.g., Ruhm, 1995; Tausig & Fenwick, 1999; Ruhm, 2000; di Tella, MacCulloch, & Oswald, 2001; Wolfers, 2003; Kahn, 2010; Bianchi 2013; Bianchi, 2016). The unemployment rate during this period ranged from a low of 3.8% in April of 2000 to a high of 6.3% in June 2003.

*Workforce entry economic conditions.* Consistent with past research, economic conditions at workforce entry were measured using the annual unemployment rate in the year each CEO earned his or her highest degree (e.g., Oyer, 2008; Kahn, 2010; Bianchi, 2013). As shown in Figure 1, economic conditions fluctuated considerably over this period, with the unemployment rate ranging from 2.9% to 9.7%.

**Control Variables**

*CEO level controls.* We included several individual level control variables that past research has shown affect the likelihood of backdating or misconduct. First, we controlled for age, using executive’s year of birth as reported in BoardEx. This is an important control for two reasons. First,
past work has shown that a CEO’s age has implications for ethical transgressions as well as risk-taking and management style (Ruegger and King, 1992; Bertrand and Schoar, 2003; Troy, Smith, and Domino, 2011). Second, the unemployment rate at workforce entry slightly increased during our sample period. Thus controlling for age allowed us to examine the unique effect of workforce economic conditions separate from monotonous time trends. In subsequent models, we also tested for the possibility of non-linear generational effects by using birth decade dummies rather than age.3

Opportunity. As discussed at the outset, one reason that CEOs may be more likely to cheat during booms is opportunity. For backdating, opportunity can be captured using stock volatility. When backdating a stock option, potential gains depend on the volatility of the stock within the reporting period. If the stock price fluctuates considerably (and some stock volatility is as high as 50%), then the gains from backdating are greater. If the stock price if fairly stable, then the gains from backdating are much less substantial. Thus, we gauged opportunity by capturing volatility in a +/- 30 day window from the option grant price.

For our imprinting analyses, we also controlled for the number of grants awarded to each executive over our sample period.

Firm controls. At the firm level we controlled for firm size. Larger firms typically have more internal controls and receive greater attention from regulators and the press (e.g. Doyle, Ge, and McVay, 2007). Consequently, executives in these firms are less likely to submit fraudulent financial

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3 We did not include CEO compensation, stock ownership, or tenure in our primary analyses because of data limitations. Our data on stock option grants came from the EDGAR system which draws from firm filings to the SEC. This dataset did not have information on compensation, stock ownership, or tenure. We attempted to match our data to compensation data from Execucomp. Because these two datasets have unique individual identifiers and use different naming conventions (e.g., PhD vs. Dr.), we employed an algorithm for exact matching based on each CEO’s name. We then manually checked the resulting names for each match. We were only able to find matches for 699 out of the 2,012 CEOs in our sample (34.7%). We lost observations for two reasons. First, while the EDGAR system draws from the entire universe of publicly-traded companies, Execucomp only covers executives from 3,300 companies. Thus, not all companies in our sample were covered in Execucomp. Second, we were unable to find exact name matches for many of the CEOs in our sample. For each CEO in our dataset for whom we were able to find a match, we gathered data for Execucomp data measuring TDC1 (log), TDC2 (log), options (log), and firm tenure. We added each of these variables to a the models shown in Table 2, Model 4 to test Hypothesis 1 and Table 3, Model 4 to test Hypothesis 2. Using this substantially reduced sample, we found marginal support for Hypothesis 1 and full support for Hypothesis 2. Adding control variables for compensation and tenure to the models shown in Table 2, Model 4, the current unemployment rate was marginally predictive of backdating (b = -0.013, SE = 0.009, p = .11). Including the control variables shown in Table 3 and adding a control for compensation and tenure, economic conditions at workforce entry were predictive of later unethical behavior (b = -0.013, SE = 0.005, p < .01). In both sets of analyses, none of the forms of compensation or tenure were significant predictors of backdating. Moreover, similar effects emerged in these restricted samples whether or not we controlled for compensation or tenure.
documents to the SEC (Bebchuk and Roe 1999; Bebchuk et al. 2010). Several measures are frequently used to capture firm size, including revenues, assets, and number of employees. For our analysis we used the log revenues of the firm, a common metric of firm size (e.g., Chatterjee and Hambrick, 2007; Schrand and Zechman, 2012; Benmelech and Frydman, 2015). We reconducted all analyses using the logged number of employees and logged total assets as measures of firm size and similar results emerged.

We also included dummy variables for industry categories using the two digit SIC codes as reported in Compustat. Backdating was more prevalent in some industries than in others, and was especially prevalent in the technology sector (Heron and Lie, 2007). Moreover, misconduct often varies across industries, in part because of differential oversight and regulations across industries (Baucus and Near, 1991; Benmelech and Frydman, 2015). In addition, we used a dummy variable to demarcate the period before and after the passage of Sarbanes-Oxley on July 30th, 2002. This act decreased the available window of time for reporting options and following its passage, the percentage of extremely lucky grant dates declined (Heron and Lie, 2007). Finally, for the imprinting analyses we controlled for the year of the option grant report. This allowed us to control for any time trends in option grants without imposing any functional form on the trend.

**Analytical Method**

We considered a suspiciously lucky grant date as an ethical transgression. Our backdating dependent variable was categorical and took the following form:

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BD_{it} = \begin{cases} 
1 & \text{if } P(i = \text{random grant})_t \leq 0.025 \\
0 & \text{if } P(i = \text{random grant})_t > 0.025 
\end{cases}
\]

\(BD_{it}\) equals 1 if a grant \(i\) at time \(t\) is has a price-date combination that is only likely to have happened randomly 2.5% of the time or less. The use of a categorical variable suggests employing a probability estimation model. For ease of interpretation we used linear probability models and reported coefficients that can be interpreted similar to an OLS model (a coefficient \(\beta\) expresses the change in probability associated with a one unit increase in \(X\)). However, since linear probability models are less efficient than linking functions based on the binomial distribution (Agresti, 2007), we ran all models with logistic model estimations. Similar results emerged using either approach.
Most of the executives in our sample received multiple grants during the period (Mean = 53.60, SD = 6.88), implying that a significant number of observations in our panel were not independent. To address the non-independence of multiple within-executive observations, we clustered all error terms at the individual CEO level and added a control variable to capture the total number of grants received by an individual in our sample. Using linear probability models and clustering the error terms at the individual level makes our estimations highly conservative. Indeed, relaxing either of these constraints greatly increases the significance of our findings.

**Results**

Table 1 includes descriptive statistics and correlations for all variables.4

---

Insert Table 1 about here

---

**Current economic conditions and backdating.** Table 2 reports the results of the linear probability models predicting backdating from individual attributes, firm attributes, and economic conditions. Model 1 shows the main effect of the unemployment rate on backdating, controlling only for industry. Consistent with Hypothesis 1, higher unemployment rates were associated with a lower likelihood of backdating stock options. Model 2 adds controls for CEO age and finds similar effects. A one unit increase in the unemployment rate was associated with a 1.7% decrease in the likelihood of backdating.

---

Insert Table 2 about here

---

In Model 3, we added a control for firm size. Consistent with past research, firm size was negatively related to backdating (Bebchuk and Roe 1999; Bebchuk et al. 2010). As previously noted, larger firms tend to have more internal controls, reputable auditors, and additional public scrutiny, all of which reduce the likelihood that executives in these firms will backdate their options (Bizjak,

---

4 Age and the unemployment rate at workforce entry are highly correlated given that economic conditions generally improved over the period examined. This correlation is significant and can create multicollinearity in our models. We address this concern by centering our age variable and testing the Variable Inflation Factor (VIF) for each model (Hair et al., 1995). In none of the models does our main predictor exceed a VIF value of 1.61.
Lemmon and Whitby, 2009). Similar results emerged. Model 4 added a control for firm returns and found similar results.

Model 5 added individual fixed effects. This allowed us to examine whether the effects were driven by other time-invariant individual differences that are not captured in our models. Similar effects emerged using this conservative test.

Model 6 added a control for opportunity. As shown in Table 1, simple correlations revealed that CEOs who were at the helm of companies with more volatile stocks were more likely to backdate their stock options. This suggests that when there was greater opportunity and more to gain, CEOs were more likely to backdate their stock options. Even after controlling for volatility, the relationship between economic conditions and backdating remained marginally significant. This suggests that opportunity explains some but not all of the increase in corporate misconduct during prosperous times.

Model 7 added a dummy variable for the passage of Sarbanes-Oxley. Since Sarbanes-Oxley passed as the economy was slowing down, including this dummy variable considerably constrains the economic variation on which we can identify. Consequently, the relationship between economic conditions and backdating no longer reached significance. This is likely due to an over-specified model. Indeed, when we removed the control for volatility which is also linked to backdating and economic conditions, the relationship between economic conditions and backdating remained significant, even after including the control for Sarbanes-Oxley.

Insert Figure 3 about here

Figure 3 plots the trends in backdating and the unemployment rate over this time period using the predicted values from the model $y = \alpha + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \epsilon$ where the dependent variable is either the unemployment rate or the proportion of backdating and time $t$ is a linear time measure at the monthly level.
To examine the magnitude of these effects, we looked at the likelihood of backdating in the best and worst economic climates. During this time period, the unemployment rate ranged from 3.8% to 6.3%, or a difference of 2.5%. For most of our models, the coefficient for unemployment was 1.7%. As previously noted, roughly 12.5% of grants in our sample were suspiciously lucky. This suggests that during the worst economic period in this sample, approximately 10.3% of stock option grants would have been backdated. Conversely, during the best economic period of this sample, approximately 14.6% of grants would have been backdated.

Ethical imprinting. Table 3 shows the results of the linear probability models predicting backdating from workforce entry economic conditions. Model 1 shows the main effect of the unemployment rate at graduation controlling for year, industry, and the number of grants the CEO received over this time period. Consistent with Hypothesis 2, CEOs who began their career in worse economic times were significantly less likely to backdate their stock options. Model 2 added a control for CEO age and found a similar negative relationship between the unemployment rate at workforce entry and backdating. A one unit increase in the unemployment rate was associated with a 0.7% decrease in the likelihood of backdating.

Model 3 added dummy variables for decade of birth rather than age to capture any generational differences in engaging in corporate misconduct. As shown in this model, there was not substantial evidence for generational differences in the likelihood of backdating. The only cohort that showed a significantly greater likelihood of backdating was the cohort born in the 1970s. However, only 4 CEOs in our sample were born in the 1970s and this pattern likely reflects the backdating behavior of a single CEO. Importantly, a similar relationship between workforce entry conditions and unethical behavior emerged using this alternative specification of age.

Model 4 added a control for firm size, which was negatively related to the likelihood of stock options being backdated. Simple correlations suggest that CEOs who graduated in prosperous times were more likely to be at the helm of large companies, a result that is consistent with past research.
(Schoar and Zuo, 2012). Yet, even though this would have made it harder to misrepresent the date a grant was actually awarded, these CEOs still showed an increased propensity to backdate.

Model 5 added a control for firm performance and found similar effects. Finally, Model 6 included controls for the current unemployment rate and volatility. Similar results emerged using these controls. The current unemployment rate did not emerge as a significant predictor in these models. This is because we included year fixed effects in these analyses and there were rarely substantial fluctuations in the monthly unemployment rate within a single year. Indeed, if we remove year fixed effects, the current unemployment rate becomes a highly significant predictor of backdating in these models.

Finally, Model 7 added a control for the passage of Sarbanes-Oxley. Similar results emerged. Indeed, across all models, CEOs who entered the workforce in prosperous times were more likely to backdate their stock option grants than CEOs who entered in worse economic times.

Again, we sought to assess the magnitude of these effects by examining the likelihood of backdating depending on the economic climate at the time a CEO entered the workforce. The difference in the unemployment rate for CEOs who graduated in the best (unemployment rate = 2.9%) rather than the worst (unemployment rate = 9.7%) economic environment over this time period was 6.8%. This suggests that for CEOs who graduated in the best economic time during this period, roughly 14.8% of their stock options would have been backdated. For CEOs who graduated during the worst economic times, this number would have fallen to 10.1%.

While our analyses provided support for both hypotheses, the effects were small. One reason for the relatively small size of these effects is that we use fairly conservative tests of unethical behavior. Indeed, we only classify an option as suspicious if it comes on one of the luckiest few days of the reporting window. This approach is likely to underestimate the magnitude of these effects.

Even so, our results suggest that small changes in corporate misconduct can have important repercussions for a firm and an individual. Executives caught backdating faced considerable fines and were likely to lose their jobs. Following backdating revelations, many companies had to restate earnings reports and pay hefty fines. Given the considerable individual and corporate implications of
being caught, even small changes in the likelihood of engaging in such behavior are likely to be economically, professionally, and organizationally meaningful.

*Interaction between Current and Workforce Entry Economic Conditions*

Finally, we tested whether current economic conditions and workforce entry economic conditions interacted to affect the likelihood of engaging in unethical behavior. Recent work has found that organizational prosperity at the time an employee joins an organization interacts with concurrent organizational resources to influence individual behavior (Tilcsik, 2014). This raised the question of whether all CEOs were more likely to cheat during prosperous times or whether the increased propensity to cheat differed depending on workforce entry economic conditions. We tested this possibility by creating an interaction term between the current unemployment rate and the unemployment rate at workforce entry and added this term to all the models shown in Table 3. This interaction term was not significant in any of the models. This null result suggests that workforce entry economic conditions affect an executive’s baseline propensity to cheat. Current economic conditions appear to raise and lower this propensity across CEOs.

*Selection*

While our analyses showed substantial support for our hypothesis that entering the workforce in prosperous times predicts later unethical behavior, there are several plausible alternative explanations for our observed effects. One plausible alternative explanation concerns selection. In a typical recession, enrollment into undergraduate and graduate programs rises as many young adults try to avoid the labor market until economic conditions improve (Kahn, 2010). This introduces the possibility that there are uncaptured differences between those who pursue additional education in recessions or prosperous times. For instance, it is likely that new graduates who are able to find a job in a recession may be particularly capable given the difficulty of securing a job during these periods. Those who are not able to find work may pursue additional degrees, raising the possibility that recession cohorts are more highly skilled. Additionally, those who started their careers in recessions may have to be unusually talented or hard-working to rise to the ranks of the CEO. While it is unclear
what, if any, implications these possible differences might have for ethical behavior, these and other selection issues suggest that there may be unobserved differences between recession and boom graduates.

We addressed this concern by estimating rather than measuring the year of workforce entry. We did this by conducting analyses in which our primary predictor was economic conditions at the typical age of graduation rather than the actual age at which executives earned their highest degrees. The majority of college graduates in the United States earn their undergraduate degrees at age 22. Since individuals do not choose their date of birth, the unemployment rate at age 22 should be unaffected by an executives’ choice to obtain additional education. Thus, economic conditions at age 22 provided one test of whether selection is driving our results.

Table 4 presents the results of models predicting backdating using this approach. Because economic conditions at age 22, age, and year are so highly related, we did not include year fixed effects in these models. As shown in Table 4, across all models, the unemployment rate at age 22 negatively predicted backdating. These analyses suggest that the relationship between economic conditions at workforce entry and ethical behavior cannot be explained by a tendency of people of varying ethical proclivities to differentially time their entry into the job market. Even so, we were not able to rule out the possibility that other selection mechanisms may be driving some of the observed effects.

General Discussion

Using a large sample of American executives and an unobtrusive indicator of unethical behavior, we found that CEOs were more likely to engage in corporate misconduct during prosperous economic times. Moreover, we found that CEOs who began their careers in prosperous times were more likely to engage in unethical behavior later in their careers. Executives who entered the workforce in an economic boom were significantly more likely to backdate their stock options to maximize their financial gains. These results could not be explained by the size of the companies they
led or the industries they occupied. Rather the conditions of their early careers predicted their propensity to misrepresent critical components of their compensation packages at a later point in life.

Our findings make several theoretical contributions to research on corporate misconduct and career imprints. Perhaps most importantly, they suggest that strong environmental conditions can affect the likelihood of traversing ethical boundaries both in the short term and, if experienced during an impressionable period, long after economic conditions have changed. Past research on precursors of corporate misconduct has focused largely on how proximal contextual signals heighten or dampen the likelihood that corporate leaders will cheat. For instance, CEOs are more likely to misrepresent company earnings if their financial incentives are linked to company performance (Bergstresser and Philippon 2006; Zhang et al., 2008). The present findings suggest that the broader economic environment, apart from an executive’s pay package and outside the organization itself, can influence the likelihood that a CEO will cheat. In doing so, it suggests that strong, diffuse situations and experiences can shape ethical behavior in the present and well into the future.

These findings also contribute to our growing understanding of the mark that early career conditions can leave on later attitudes and behaviors. Past work has shown that CEO’s who begin their careers in prosperous times tend to run larger companies, are more likely to move across companies and industries, and employ more aggressive financial strategies (Schoar and Zuo, 2012). The present results suggest that early career economic conditions also predict the likelihood of ethical missteps later in life. Given the substantial organizational and personal costs of executive misconduct, these findings are both practically and theoretically important (Peng and Roell, 2008; Pfarrer et al, 2008; Wiesenfeld, Wurthmann, and Hambrick, 2008).

These findings also contribute to our understanding of how ethical norms and ethos develop. Past work on the formation of ethical systems has suggested that childhood families are the primary vehicle through which moral attitudes are transmitted (e.g. Kohlberg and Kramer, 1969; Noe and Rebello, 1994). Other work has highlighted the role of educational institutions in shaping moral values (e.g., Akerloff, 1983). The current findings suggest that strong experiences outside of childhood and apart from formal education also influence the moral proclivities of corporate leaders.
In doing so, it builds on a growing body of work suggesting that strong experiences in early adulthood can shape ethical behavior in later life (e.g. Benmelech and Frydman, 2015).

Our work also highlights the relative malleability of ethical behavior to concurrent economic conditions. Indeed, when the economy was doing well, all CEOs in our sample were more likely to engage in backdating, even those who first began their careers in a recession. This suggests that early experiences appear to influence one’s baseline propensity to cheat but concurrent economic conditions can move this starting point up or down.

Limitations and future directions

While our work uses a large sample of American executives and unobtrusively charts behavior over ten years, it does have several limitations which also point to fruitful areas for future research. First, the examined period consisted of only modest fluctuations in economic conditions which allowed a somewhat constrained test of Hypothesis 1. On the one hand, significant results in this context suggest that even small economic changes can have meaningful implications for ethical behavior. On the other hand, economic conditions never became particularly dire during this time period. Thus it is unclear whether a deeper downturn would continue to yield ethical improvements.

Second, while we suggest that beginning one’s career in prosperous times affects the mental models new entrants form about ethically acceptable practices and norms, there are other potential explanations for these results. For instance, because our inquiry is limited to the business world, it is possible that unexamined selection variables account for our results.

Finally, future work could elucidate exactly how workforce entry economic conditions imprint the ethical leanings of young workers. Our reasoning points to two potential mechanisms. First, it suggests that workforce entrants are more likely to be exposed to ethically-questionable behavior during booms and thus are more likely to view such questionable practices as acceptable and normative. Second, it suggests that beginning one’s career amidst a wealth of opportunities may evoke a mentality of overconfidence and risk-taking that is more conducive to cheating. Future research could tease apart these mechanisms. One way to do this would be to follow a CEO’s career progression over time. Scholars could then examine whether boom time graduates who begin their careers in ethically-suspect organizations carry stronger imprints than those who begin in more
ethically responsible firms. Supportive evidence would suggest that direct exposure to unethical practices rather than a general mentality of deservingness are driving these effects. Such inquires could continue to clarify when and how those who enter the workforce in prosperous times are more likely to behave unethically later on.
References


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Figure 1. The Number of CEOs by Workforce Entry Year and the National Unemployment Rate, 1948-2005
Figure 2. An illustration of the identification strategy for suspiciously lucky grants using the stock price around a grant date for Gregory Reyes, CEO of Broadcom Corporation.

The chart shows the Broadcom’s Stock Price from 4/26/00 to 6/21/00. The mean price of a random grant, $\mu(P_t)$, is indicated by a horizontal line. The 95% confidence interval of a random grant is calculated as $\mu(P_t) \pm 1.96\sigma(P_t)$. The graph also highlights suspiciously lucky grants, which are unlikely to happen by chance.
Figure 3. Polynomial Trend of the Proportion of Suspiciously Lucky Stock Option Grants and the National Unemployment Rate by Month, 1996-2005.
Table 1. Correlations and Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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<td>1. Backdate</td>
<td>0.15</td>
<td>0.35</td>
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<td>2. Current Unemployment Rate</td>
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<td>0.69</td>
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<td>5. Firm size (Annual revenues log)</td>
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<td>-0.110</td>
<td>0.185</td>
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<td>6. ROA (log)</td>
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<td>-0.051</td>
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<td>0.105</td>
<td>0.332</td>
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<td>7. Number of grants per individual</td>
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<td>20.97</td>
<td>-0.053</td>
<td>-0.072</td>
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<td>0.079</td>
<td>0.333</td>
<td>0.102</td>
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<td>8. Volatility</td>
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<td>1.95</td>
<td>0.072</td>
<td>-0.214</td>
<td>-0.020</td>
<td>-0.014</td>
<td>0.166</td>
<td>0.061</td>
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<td>9. Sarbanes-Oxley</td>
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<td>0.47</td>
<td>-0.026</td>
<td>0.643</td>
<td>0.135</td>
<td>0.052</td>
<td>-0.031</td>
<td>-0.037</td>
<td>-0.117</td>
<td>-0.165</td>
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All correlations |.03| p < .01
Table 2. Linear Probability Model of the Likelihood of Backdating by Monthly Unemployment Rate.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
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<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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<td>Current Unemployment Rate</td>
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<td>-0.017**</td>
<td>-0.018***</td>
<td>-0.017**</td>
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<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
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<td>(0.001)</td>
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<td>(0.002)</td>
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<td>ROA (lagged)</td>
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<td>Constant</td>
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<td>(R^2)</td>
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<td>0.017</td>
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\* p<0.05, \*\* p<0.01, \*\*\* p<0.001
Robust standard errors, clustered by individual, are in parentheses.
Table 3. Linear Probability Model of Backdating by Workforce Entry Economic Conditions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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<tr>
<td>Workforce entry unemployment rate</td>
<td>-0.005†</td>
<td>-0.007*</td>
<td>-0.009*</td>
<td>-0.007*</td>
<td>-0.007*</td>
<td>-0.006*</td>
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<td>-0.001</td>
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<td>Birth decade 1940s (N = 863)</td>
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<td>Birth decade 1960s (N = 191)</td>
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<td>Birth decade 1970s (N = 4)</td>
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<td>-0.008***</td>
<td>-0.010***</td>
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<td>-0.010**</td>
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* p<0.01, ** p<0.001, *** p<0.05
Robust standard errors, clustered by individual, are in parentheses
Table 4. Linear Probability Models of Backdating Using the Unemployment at Age 22 to Instrument Workforce Entry Economic Conditions

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<th>Model 1</th>
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*** p<0.001, ** p<0.01, * p<0.05, † p<0.1
Robust standard errors, clustered by individual, are in parentheses