ESSAYS IN LABOR ECONOMICS

by

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DISSERTATION ABSTRACT

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I model a hiring process in which a candidate is evaluated sequentially by two agents of a firm. Each agent observes an independent signal of the candidate's productivity. I show that if the second agent values a non-productive attribute of a given candidate, that candidate may be less likely to be hired than a candidate lacking the preferred non-productive attribute due to the first agent adjusting their own quality threshold to compensate. I go on to empirically explore the behavior of prisoners in Oregon based on exogenous shocks to the status quo. These shocks include changes in the generosity of sentence reductions available to certain prisoners and the implementation of a variety of policies that have made it less costly for prisoners to communicate with the outside world. I find that prisoners respond to behavioral reviews with improved behavior on the days immediately before and after a review, but increasing available sentence reductions awarded for good behavior does not reduce misconduct rates among inmates. Furthermore, I find that increasing the ability of prisoners to communicate with friends and family using technology has not led to the decrease in in-person visitation that many have predicted. Instead, total communication seems to have increased in Oregon prisons. Given the extensive literature that suggests increased communication with the outside world reduces a prisoner's likelihood of recidivating, this result may indicate that introducing communication technology and making it more affordable may be a cost effective policy to prevent future crimes.

This dissertation includes unpublished co-authored material.

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This work is dedicated to my amazing wife Kari.

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CHAPTER I

INTRODUCTION

Labor economics encompasses a variety of topics that assess how and whether individuals respond to incentives. This work is designed to further our understanding of that process using both theoretical and empirical analysis. Chapters II, III, and IV are co-authored. Glen Waddell is my co-author for Chapter II while both Glen Waddell and Ben Hansen are co-authors for Chapters III and IV.

In Chapter II, I develop a model of a hiring process in which the candidate is evaluated sequentially by two agents of the firm who each observe an independent signal of the candidate's productivity. I introduce the potential for taste-based discrimination and characterize how one agent's private valuation of the candidate influences the other agent's hiring practices. This influence is often in an offsetting direction and is partially corrective. Yet, this offsetting response can also be large enough that even a high-productivity candidate who is privately favored by one agent is less likely to be hired even when the other agent has no preference over private attributes.

I use administrative data from the Oregon Department of Corrections to measure prisoner responses to incentives for good behavior in Chapter III. Namely, I take advantage of 50% increase in the generosity of sentence reductions offered to prisoners convicted of certain crimes in Oregon. In addition, I also explore the effects of discontinuous shifts in the expected return to good behavior offered by the six-month assessment periods in which prisoners are awarded sentence reductions. My results suggest that prisoners are not responsive to either sentence reduction based incentive with misconduct rates remaining unchanged in each case. The one exception to this finding is that inmates do improve their behavior on the day immediately prior to and the day immediately following an assessment. Broadly, the evidence is consistent with highly myopic prisoners who respond to incentives only when a payoff is immediately realized or has very recently been realized.

Finally, In Chapter IV, I investigate the effect of technological changes which reduced the costs and provided alternative means for prisoners to communicate with friends or family. Utilizing administrative records on the universe of the incarcerated population in Oregon and daily level administrative data on both prisoner visitation and misconducts, I construct a panel of over 21,000,000 prisoner days. Taking advantage of a state-wide decrease in long-distance rates, the introduction of video chatting and delayed messaging, and an unexpected permanent decrease in the price of video chat services, I find evidence that reducing the price of outside communication increases the use of that form of communication with little or no substitution effects occurring across communication types. The criminology literature suggests that increased contact with the outside world should improve behavior both while prisoners are incarcerated and after they are released in the form of reduced recidivism rates. Chapter V offers concluding comments.

CHAPTER II

THE TIMING OF DISCRIMINATION IN SEQUENTIAL HIRING GAMES

This chapter is a component part of co-authored work with Glen R. Waddell in which I am a full participant.

Introduction

Gender and race gaps in wages and employment persist in U.S. and global labor markets. While experimental evidence supports taste-based racial discrimination as a direct contributor (Bertrand and Mullainathan, 2004; Carlsson and Rooth, 2011; Castillo, Petie, Torero, and Vesterlund, 2013), incomplete information can also give rise to statistical discrimination (Altonji and Pierret, 2001; Farber and Gibbons, 1996; Aigner and Cain, 1977). We consider a mechanism at the intersection of these areas.

We do this in a setting where two agents of the firm participate in a sequential evaluation of a job candidate. We then consider the implications of agents experiencing private benefits or costs associated with an observable but non-productive attribute of the candidate (e.g., race, gender). As such, we have a structure that nicely captures either "bottom-up" or "top-down" efforts to increase racial diversity, for example, or the presence of females. Of course, the implications of any such efforts in this sort of mechanism are not well understood. As such, holding the sequential nature of evaluation constant—an initial screening followed by further consideration if the initial screening goes well—we vary *where* in the sequence and to what degree the candidate's non-productive attribute is valued. Among our results, we show that where pro-diversity interests are stronger at the top of the institution, acting on such preference may be limited in its ability to narrow gaps in outcomes across race or gender, and may even contribute to *increasing* wage and employment gaps. Thus, in this setting, even preference *for* some non-productive attribute in a job candidate can be to the candidate's detriment. Moreover, we show that those at the top of the institution with the preference to hire with race or gender in mind, are likely to be insufficiently equipped to incentivize cooperation from those below.

The setting we consider is rich enough to capture the relevant tradeoffs yet sufficiently straightforward that we can speak effectively to policy. We abstract away from the role of committees, for example, and consider only individual agents, two in number, and acting in sequence on behalf of the firm or institution. We assume that the candidate is considered by the second agent (have in mind the firm's owner, for example, although one could imagine university administrator also fitting well) only when the first agent (a division manager, for example, or a department chair) has determined that the candidate is worthy of forwarding in the search. In that way, the process we model captures the typical "up or out" nature of job searches.[1]

Becker (1957) first introduced an economic model of discrimination in which employers had a taste for discrimination, insofar as there was a disamenity to employing minority workers who would have to compensate employers by being more productive at a given wage or being willing to accept a lower wage for identical productivity. Elements of this intuition will remain in our model, although the implications will now depend on where in the sequence such a disamenity is introduced—whether it is introduced "early" or "late." Elements of the longer literature will also be evident in what follows as we reconsider the role of private valuations amid uncertainty around worker productivity (Arrow, 1971; Phelps, 1972; McCall, 1972; Arrow, 1973; Spence, 1973).[2]

In terms of actionable policy, we will speak directly to the implications of directed searches—where private values are arguably a stronger motivating factor at the top of the firm's hierarchy. We will refer to these preferences as "top-down," and demonstrate that in such environments, early decision makers will often take positions that offset the anticipated preferences of later decision makers. In the limit, when the late-arriving preference *for* the personal attribute is large, this "offsetting" effect is sufficient to leave even the high-productivity candidates from the privately preferred group worse off; facing a *lower* probability of employment. For example, where leadership values female candidates, highly productive female applicants are

[1]Green and Laffont (1987) model a two-person decision problem but assume away a hierarchy of agents. Similarly, Luo (2002) considers collective decision making in a two-person model where agents collaboratively to make decisions.

[2]In other related work, Eriksson and Lagerström (2012) use a resume study in Norway to show candidates who have non-Nordic names, are unemployed, or older receive significantly fewer firm contacts. Kuhn and Shen (2013) find that job postings in China that explicitly seek a certain gender, while suggestive that firms have preferences for particular job-gender matches, only play a significant role in hiring decisions for positions that require relatively little skill. Jacquemet and Yannelis (2012) discuss whether observed bias is due to discrimination against a particular group or favoritism for another group. Other explanations for gender and race gaps include firms benefitting from increased productivity when workforces are homogenous (Breit and Horowitz, 1995), and in-group-favoritism effects (Lewis and Sherman, 2003). Pinkston (2005) introduces the role for differentials in signal variance (e.g., black men have noisier signals of ability than white men) into a model of statistical discrimination. Ewens, Tomlin, and Wang (2014) consider separating statistical discrimination from taste-based discrimination and find support for statistical discrimination in rental markets. For a review of the evolution of empirical work on discrimination, see Guryan and Charles (2013).

harmed by early decision makers protecting their interest against the anticipation of favorable treatment in subsequent rounds. In no way is this due to a disutility associated with hiring a candidate with a particular attribute (e.g., we do not need the first agent to dislike female candidates to find that female candidates can be made worse off when favored by the second agent) but is solely due to agents having incomplete information of candidates' true abilities and the requisite tradeoffs being made at the margin when the early mover anticipates a candidate-favoring bias being introduced by subsequent decision makers. Thus, one might fear that policies designed to encourage the hiring of workers who increase workforce diversity can promote even the opposite outcome if agents of the firm (particularly those acting early in hiring decisions) do not share equally in those interests.

This tension between the first and second decision makers is fundamental. As such, we consider comparative statics around these margins, varying the private values introduced by the first and second agents as we consider the implications on employment and workforce productivity. As private values influence the relative probabilities with which candidates of different abilities are hired, we will also discuss the distributional consequences for subsequent promotion games.

In Section 2.2 we introduce the model we have in mind, solving the sequential consideration of agents backwards. Throughout, we consider private values of either sign although cases in which candidates are "favored" somewhere in the hiring process may be the more relevant to policy, especially where we demonstrate that this can be to their detriment. We do this in two settings.

In Section 2.3 we consider a setting in which the second agent in the sequence is somewhat "naive" in forming his expectations of the first agent's action—not expecting that the first agent may respond to the second agent's private incentives. For example, university leadership may reveal that they favor female or minority candidates at the margin and fully expect that departments will not work to oppose these interests. Yet, as long as there is the potential for departments to value those non-productive attributes differently, interests can be in conflict. In particular, we discuss the model's implications in light of the asymmetries in how early and late decision makers can influence outcomes when agents are moving in sequence, including subsequent promotion games and the role of incentive pay.

In Section 2.4 we consider a setting in which Agent 2 is "savvy" regarding Agent 1's incentives, and fully anticipates this in his own optimization routine. While we tend to think that those in leadership positions (university deans, for example) may fall short of fully anticipating how others (department committees) might respond to "top-down" directives, we offer additional intuition by considering outcomes spanning these settings. It is in this setting that we consider whether the second decision maker can incentivize the first in a way that sufficiently aligns their private valuations of the non-productive attribute.

In Section 2.5 we offer concluding remarks.

Theory

The Setup

We are intent on considering the implications of agents having private values associated with some non-productive attribute of a job candidate as they undertake the hiring responsibilities for the firm. In so doing, we consider a two-stage hiring game in order to speak to the implications of these private values being introduced to the hiring process at different stages. By assumption, Agent 1 considers the candidate first and either rejects the candidate or forwards the candidate to Agent 2 for further consideration. If forwarded, Agent 2 can then reject or hire the candidate. Within such a hierarchy, we then consider private valuations: "bottom-up" preferences (e.g., grass roots efforts to increase racial diversity among co-workers), or "top-down" preferences (e.g., a university administrator's preference to increase the presence of female faculty in STEM fields), or combinations thereof.[3]

As a candidate's productivity is not verifiable, both agents only know that with probability $\alpha \in (0, 1)$ a given candidate is highly productive and would therefore be "good" for the firm. We quantify the upside to hiring such a candidate as an increase in the firm's value from V_0 to V_g. With probability $(1 - \alpha)$ the candidate's productivity is such that hiring the candidate would be "bad" for the firm and would decrease the firm's value from V_0 to V_b. In such a case, the firm is always best served by rejecting the candidate, in which case the firm's value would remain at the status-quo level, V_0. Without loss of generality, we assume that $V_0 = 0$.

[3]STEM: Science, Technology, Engineering, and Mathematics.

It is uninteresting to consider compensation schemes that do not tie remuneration to agents' actions. That said, these weights are determined outside the model and we simply parameterize these relationships in Agent 1 receiving $\tau_1 \in (0,1)$ of the value to the firm and Agent 2 receiving $\tau_2 \in (0,1)$, such that $\tau_1 + \tau_2 \leq 1$. As agents are moving in strict sequence, consistent with a hierarchy, it may be reasonable to further anticipate that $\tau_1 \leq \tau_2$.[4]

We introduce the potential for discrimination and favoritism by allowing for some non-productive but verifiable attribute of the candidate to be privately valued by either or both agents. Given the sequence of actions, we notate any private benefits accruing to Agent 1 from hiring the candidate as B_1, and any private benefits accruing to Agent 2 as B_2. To maintain interest and relevance, we will limit agents' private values to those that yield interior solutions.[5] That is, we will limit private values to those that do not have the agents' first-order conditions collapse to "always reject" or "always accept." The model can be solved backwards.

Agent 2's Problem

When the candidate is forwarded to Agent 2 for final consideration, Agent 2 draws an independent signal of the candidate's productivity. The signal, s_2, is drawn from $N(\mu_b, \sigma_b)$ if the candidate is a "bad" type, and from $N(\mu_g, \sigma_g)$ if the candidate is a "good" type, where $\mu_b < \mu_g$. $F_b(\cdot)$ is the CDF of $N(\mu_b, \sigma_b)$ and $F_g(\cdot)$ is the CDF of $N(\mu_g, \sigma_g)$.[6] With such a setup, Agent 2's decision rule can then be summarized in the choice of a reservation signal, $\hat{s}_2$. If the realized signal, s_2, is higher than the chosen reservation signal, $\hat{s}_2$, the candidate is hired. If $s_2 < \hat{s}_2$, the candidate is rejected and no hire is made.

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[4]For some context regarding the use of incentive pay broadly, see Murphy (2013).

[5]Assuming that $\tau_1 V_b \leq B_1 \leq \tau_1 V_g$, and $\tau_2 V_b \leq B_2 \leq \tau_2 V_g$ effectively limits the set of values where an agent has these dominant strategies to just those where $B_i = \tau_i V_b$ or $B_i = \tau_i V_g$, respectively. More generally, the range of private values over which interesting interactions occur depends on the payoff levels to agents relative to these private values. That is, in the symmetric case, where $B_i > \tau_i V_g$, Agent i will adopt an "always-accept" strategy. Likewise, where $B_i < \tau_i V_b$, Agent i will adopt an "always-reject" strategy.

[6]Lang and Manove (2011) suggest that employers find it more difficult to evaluate the productivity of black candidates than white candidates. This would imply that non-productive attributes may be correlated with signal noise. Our model can easily encompass this potential by allowing σ_b and σ_g to vary with the candidate's non-productive attribute.

Formally, Agent 2's objective equation can be written as,

$$
\begin{aligned}
\underset{\hat{s}_2}{\text{Max}}\, V_2(\hat{s}_2) \quad = \quad & \alpha[F_g(\mathbb{E}_2[\hat{s}_1]) + (1 - F_g(\mathbb{E}_2[\hat{s}_1]))F_g(\hat{s}_2)]\tau_2 V_0 \\
& +\alpha(1 - F_g(\mathbb{E}_2[\hat{s}_1])(1 - F_g(\hat{s}_2))(\tau_2 V_g + B_2) \\
& +(1-\alpha)[F_b(\mathbb{E}_2[\hat{s}_1]) + (1 - F_b(\mathbb{E}_2[\hat{s}_1])F_b(\hat{s}_2)]\tau_2 V_0 \\
& +(1-\alpha)(1 - F_b(\mathbb{E}_2[\hat{s}_1]))(1 - F_b(\hat{s}_2))(\tau_2 V_b + B_2).
\end{aligned} \tag{2.1}
$$

As Agent 2 only considers the candidate upon her having successfully navigated Agent 1's evaluation, the probability Agent 2 puts on the candidate being highly productive is updated from the population parameter, α, to reflect Agent 1's evaluation (i.e., that s_1 must have been no smaller than $\hat{s}_1$). Each term in (2.1) therefore represents the probability weighted outcomes of the hiring game—the candidate is either a good candidate but not hired (Agent 2 realizes $\tau_2 V_0$), good and hired ($\tau_2 V_g + B_2$), bad and not hired ($\tau_2 V_0$), or bad and hired ($\tau_2 V_b + B_2$). While the true conditional probability depends on Agent 1's reservation signal, $\hat{s}_1$, what matters to characterizing Agent 2's choice is his belief about what Agent 1's reservation signal was in the first stage, which we capture as $\mathbb{E}_2[\hat{s}_1]$.[7]

Given (2.1), Agent 2's choice of $\hat{s}_2$ solves the first-order condition,

$$
\frac{\alpha(1 - F_g(\mathbb{E}_2[\hat{s}_1]))f_g(\hat{s}_2)}{(1-\alpha)(1 - F_b(\mathbb{E}_2[\hat{s}_1]))f_b(\hat{s}_2)} = \frac{\tau_2 V_0 - (\tau_2 V_b + B_2)}{(\tau_2 V_g + B_2) - \tau_2 V_0}. \tag{2.2}
$$

That is, in equilibrium Agent 2's optimal reservation signal, $\hat{s}_2^\star$, equates the ratio of probabilities of committing type-I and type-II errors (i.e., $\alpha(1 - F_g(\mathbb{E}_2[\hat{s}_1]))f_g(\hat{s}_2)$, and $(1-\alpha)(1 - F_b(\mathbb{E}_2[\hat{s}_1])f_b(\hat{s}_2)$, respectively) with the ratio of costs (i.e., $(\tau_2 V_g + B_2) - \tau_2 V_0$, and $\tau_2 V_0 - (\tau_2 V_b + B_2))$.

Agent 1's Problem

In the first stage, Agent 1 draws an independent signal, s_1, of the candidate's productivity to be compared to a chosen reservation signal, $\hat{s}_1$. As above, the candidate's signal of productivity,

[7] Agent 2's expectation of the probability a good candidate cleared Agent 1's reservation is therefore $1 - F_g(\mathbb{E}_2[\hat{s}_1])$, while the expectation of the probability a bad candidate cleared Agent 1's reservation signal is $1 - F_b(\mathbb{E}_2[\hat{s}_1])$.

s_1, is drawn from $N(\mu_b, \sigma_b)$ if the candidate is a "bad" type and from $N(\mu_g, \sigma_g)$ if the candidate is a "good" type. If $s_1 < \hat{s}_1$, the candidate's file is immediately abandoned and no hire is made—Agent 2 never sees the candidate and the resulting firm value is V_0. If $s_1 \geq \hat{s}_1$, the candidate is then subjected to consideration by Agent 2, as described in Equation (2.2).

Where $R_2(\mathbb{E}_2[\hat{s}_1])$ captures Agent 2's choice of $\hat{s}_2$ given his expectation of $\hat{s}_1$, Agent 1's objective equation can be written,

$$\begin{aligned}
\underset{\hat{s}_1}{\text{Max}}\, V_1(\hat{s}_1) &= \alpha[F_g(\hat{s}_1) + (1 - F_g(\hat{s}_1))F_g(R_2)]\tau_1 V_0 \\
&\quad + \alpha(1 - F_g(\hat{s}_1))(1 - F_g(R_2))(\tau_1 V_g + B_1) \\
&\quad + (1 - \alpha)[F_b(\hat{s}_1) + (1 - F_b(\hat{s}_1))F_b(R_2)]\tau_1 V_0 \\
&\quad + (1 - \alpha)(1 - F_b(\hat{s}_1))(1 - F_b(R_2))(\tau_1 V_b + B_1).
\end{aligned} \tag{2.3}$$

where we capture in B_1 any private value Agent 1 associates with the candidate's non-productive attribute. In general, Agent 1 chooses $\hat{s}_1$ subject to the first-order condition,

$$\frac{\alpha f_g(\hat{s}_1)(1 - F_g(R_2)) + \alpha(1 - F_g(\hat{s}_1))f_g(R_2)(\partial R_2/\partial \hat{s}_1)}{(1 - \alpha)f_b(\hat{s}_1)(1 - F_b(R_2)) + (1 - \alpha)(1 - F_b(\hat{s}_1))f_b(R_2)(\partial R_2/\partial \hat{s}_1)} \tag{2.4}$$

$$= \frac{\tau_1 V_0 - (\tau_1 V_b + B_1)}{(\tau_1 V_g + B_1) - \tau_1 V_0}. \tag{2.5}$$

As above, Agent 1 chooses his optimal reservation signal, $\hat{s}_1^\star$, to equate the ratio of probabilities of committing type-I and type-II errors with the ratio of costs.[8]

In Section 2.4 we consider the case where Agent 2 is savvy—that is, he correctly anticipates how Agent 1 best responds to $B_2 \neq 0$—and Agent 1 likewise considers Agent 2's best response when choosing $\hat{s}_1$. While this alters the optimal $\hat{s}_1$ and $\hat{s}_2$ profiles for a range of B_2 values, the original result remains—large positive values of B_2 make the "preferred" group less likely to be hired.

[8] This is easy to see in the symmetric case (i.e., $V_b = -V_g$, $V_0 = 0$, and $\alpha = 0.5$), as Agent 2's first-order condition collapses to $f_g(\hat{s}_2) = f_b(\hat{s}_2)$.

When Agent 2 Is Naive

Agent Behavior

In this section, we begin with the consideration of strictly "top-down" preferences (i.e., $B_2 \neq 0$ while $B_1 = 0$), which is consistent with Agent 1 being interested only in the productivity of the candidate while Agent 2 has private objectives associated with hiring, such as to increase the representation of certain races or gender of worker (i.e., $B_2 > 0$).

We model Agent 2's naiveté by setting his expectation of Agent 1's reservation signal, $\mathbb{E}_2[\hat{s}_1]$, equal to what Agent 1 would choose in the absence of any private values (i.e., as if $B_2 = 0$). In particular, this is akin to Agent 2 not anticipating that Agent 1 will consider B_2 when choosing $\hat{s}_1$. When $\mathbb{E}_2[\hat{s}_1] = \hat{s}_1^\star|_{B_2=0}$, Agent 2's first-order condition in (2.2) simplifies to

$$\frac{\alpha(1 - F_g(\hat{s}_1^\star|_{B_2=0}))f_g(\hat{s}_2)}{(1-\alpha)(1 - F_b(\hat{s}_1^\star|_{B_2=0}))f_b(\hat{s}_2)} = \frac{\tau_2 V_0 - (\tau_2 V_b + B_2)}{(\tau_2 V_g + B_2) - \tau_2 V_0}, \tag{2.6}$$

and $\hat{s}_2^\star$ depends on the expectation of Agent 1's reservation signal, here set to $\hat{s}_1^\star|_{B_2=0}$, constant in B_2.

That $\mathbb{E}_2[\hat{s}_1] = \hat{s}_1^\star|_{B_2=0}$ also implies that $\partial R_2(\mathbb{E}_2[\hat{s}_1])/\partial \hat{s}_1 = 0$. As Agent 1 finds neither private cost nor private benefit in the non-productive attribute of the candidate (i.e., $B_1 = 0$), τ_1 drops from the agent's problem, and Agent 1's first-order condition in (2.5) simplifies to

$$\frac{\alpha f_g(\hat{s}_1)(1 - F_g(R_2(\hat{s}_1|_{B_2=0})))}{(1-\alpha) f_b(\hat{s}_1)(1 - F_b(R_2(\hat{s}_1|_{B_2=0})))} = \frac{V_0 - V_b}{V_g - V_0}. \tag{2.7}$$

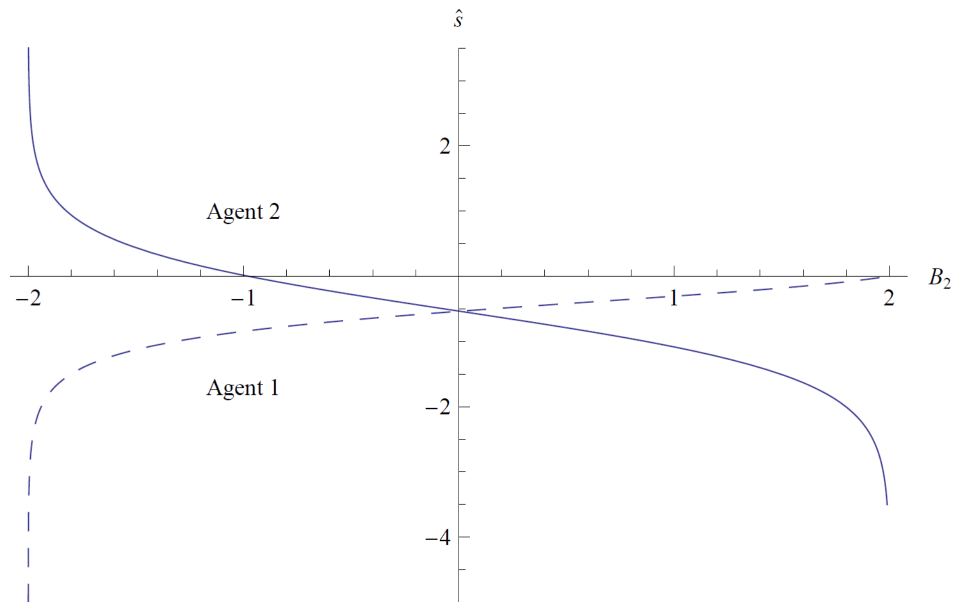
which will vary with B_2 through its effect on $R_2(\cdot)$.

In Figure 2.1 we illustrate the tradeoffs in the sequential screening of candidates by plotting the optimally chosen $\hat{s}_1^\star$ and $\hat{s}_2^\star$ across a range of B_2 between $\tau_2 V_b$ (where the private cost to Agent 2 of hiring someone with this attribute completely offsets the benefit of hiring a "good" worker) and $\tau_2 V_g$ (where the private benefit to Agent 2 of hiring someone with this attribute completely offsets the cost of hiring a "bad" worker). For illustrative purposes, we impose *ex ante* symmetry.[9] Initially, we also abstract away from the role of incentive pay in agent behavior by

[9] Symmetry is defined as $V_b = -V_g$, $V_0 = 0$, and $\alpha = 0.5$. Collectively, the first-order condition for the choice of $\hat{s}_2$ is clear, as $f_g = f_b$ in equilibrium. In characterizing agent behavior, we adopt that $V_b = -4$, $V_g = 4$, $\mu_g = 1$, $\mu_b = -1$, and $\sigma_g = \sigma_b = 1$.

setting $\tau_1 = \tau_2 = 0.5$. As changes in τ_1 and τ_2 determine the relative weights the private values play in agent decisions (i.e., where τ_i is large, Agent i's incentives are better aligned with the firm's) we will return to consider these margins below.

FIGURE 2.1. Optimal Reservation Signals With a Naive Agent 2



As illustrated in Figure 2.1, where B_2 decreases from zero and hiring the candidate imposes greater private costs on Agent 2, Agent 2 chooses a higher reservation signal, which is consistent with the agent's incentive to make it less likely that such a candidate successfully clears the required standard. While this exposes the firm to higher odds of making a type-I error (i.e., rejecting a good candidate) the perspective of Agent 2 is that the private costs of hiring an individual with the non-productive attribute are offset by the higher probability that the candidate is a good hire. That Agent 2 is motivated by this private value is clearly costly to the firm. Of course, any increase in B_2 from zero is also costly to the firm, as Agent 2 chooses a lower reservation signal in an attempt to increase the probability that the candidate is hired, where B_2 would be realized. This exposes the firm to higher odds of making a type-II error (i.e., hiring a bad candidate).

Figure 2.1 also reveals two interesting limiting cases in $B_2 = \tau_2 V_b$ and $B_2 = \tau_2 V_g$, where Agent 2's decision rule collapses on either "never hire" or "always hire." Again, this is in keeping with expectations. Where $B_2 = \tau_2 V_b$, the private cost associated with the non-productive attribute is sufficiently high that there is no possible outcome available (i.e., even $\tau_2 V_g$ is not sufficiently high) that would dominate the status quo of $\tau_2 V_0$ net of B_2. Likewise, where $B_2 = \tau_2 V_g$, the private benefit to the non-productive attribute is sufficiently high that there is no possible outcome available (i.e., even $\tau_2 V_b$ is not sufficiently low) that would dominate the potential that a "bad" hire is made and the firm realizes a value of $\tau_2 V_b$.[10]

The shape of Agent 1's choice of $\hat{s}_1^\star$ across B_2 is where we first observe the behavior of consequence. First, as Agent 1 anticipates how $\hat{s}_2^\star$ varies with B_2, Agent 1's first-order condition in (2.7) implies that he adopts a *higher* reservation signal when B_2 is higher, requiring less uncertainty regarding the candidate's type before forwarding the candidate to Agent 2 where Agent 2 will be excessively favorable toward the candidate.

Proposition 1. *With top-down preferences, for any $|B_2| > 0$ Agent 1's choice of reservation signal acts as a weakly corrective force. That is, Agent 1's mitigating influence on firm value is non-negative as long as $|B_2| > 0$.*

Moreover, as B_2 approaches $\tau_2 V_g$ and Agent 2's decision rule collapses to the unproductive act of "always accepting" a candidate who provides the privately valued attribute, Agent 1's decision rule collapses to that which would be chosen by a single decision maker facing the same uncertainty (i.e., $\hat{s}_1^\star = 0$). In effect, while Agent 1's best response to Agent 2 favoring the candidate is corrective and valuable to the firm in expectation (i.e., it limits the potential losses that would otherwise result), Agent 2's private interest completely consumes the gains provided to the firm from having the second signal of the candidate's productivity.[11]

However, this "corrective" ability of Agent 1 is not symmetric around $B_2 = 0$. As the private *costs* to Agent 2 increase and B_2 approaches $\tau_2 V_b$, Agent 2 never hires the candidate and Agent 1's choice is of no consequence to outcomes. The sequential nature of the hiring decision essentially limits the influence Agent 1 can have in offsetting $B_2 < 0$ and, in the limit, the firm suffers an unmitigated cost from Agent 2's bias. Again, this private cost results in the value to the firm created by the multiple signals of productivity being completely dissipated.

[10] Though not reported, all results have been supported by numerical simulations that verify the theoretical outcomes.

[11] Note that with symmetry assumed, a single decision maker would solve the first-order condition at $\hat{s} = 0$. In Figure 2.1, that $\hat{s}_1^\star < 0$ when $B_2 = 0$ is a reflection of the value to the firm of having a second agent. Agent 1 can adopt a lower reservation signal anticipating that Agent 2's independent draw and evaluation is pending. (While particularly evident at $B_2 = 0$, this is also driving the general result that $\hat{s}_1^* \leq 0$.)

Implications for Employment and Firm Value

In Panel A of Figure 2.2 we plot, across B_2, the employment rates associated with Agent 2 acting alone. While any observable attribute would work, we plot the relative treatments of gendered candidates, with the private value (B_2 in this case) capturing the private value associated with a female candidate. Clearly, without any offsetting influence of Agent 1, as B_2 increases from zero the probability a low-productivity female is hired clearly increases at a faster rate than does the probability a high-productivity female is hired. While optimal for Agent 2, this is destructive to firm value as this implies that the average productivity of female workers is falling. Likewise, as B_2 decreases from zero (and female hires are privately costly) the probability a low-productivity female is hired decreases at a slower rate than does the probability a high-productivity female is hired. This again decreases the value of the firm.

In Panel B of Figure 2.2, we plot employment rates across B_2, but with Agent 1 now actively participating in the hiring game. Relative to Agent 2 acting alone, the offsetting and corrective influence (from the firm's perspective) of Agent 1 is immediately evident. In fact, for both high- and low-productivity candidates, there is now significantly less separation in employment probabilities by gender, across all B_2 other than in the limiting case of $B_2 = \tau_2 V_b$. For high B_2 (i.e., those in the vicinity of $\tau_2 V_g$), high-productivity candidates can be strictly worse off than they would be without preference.

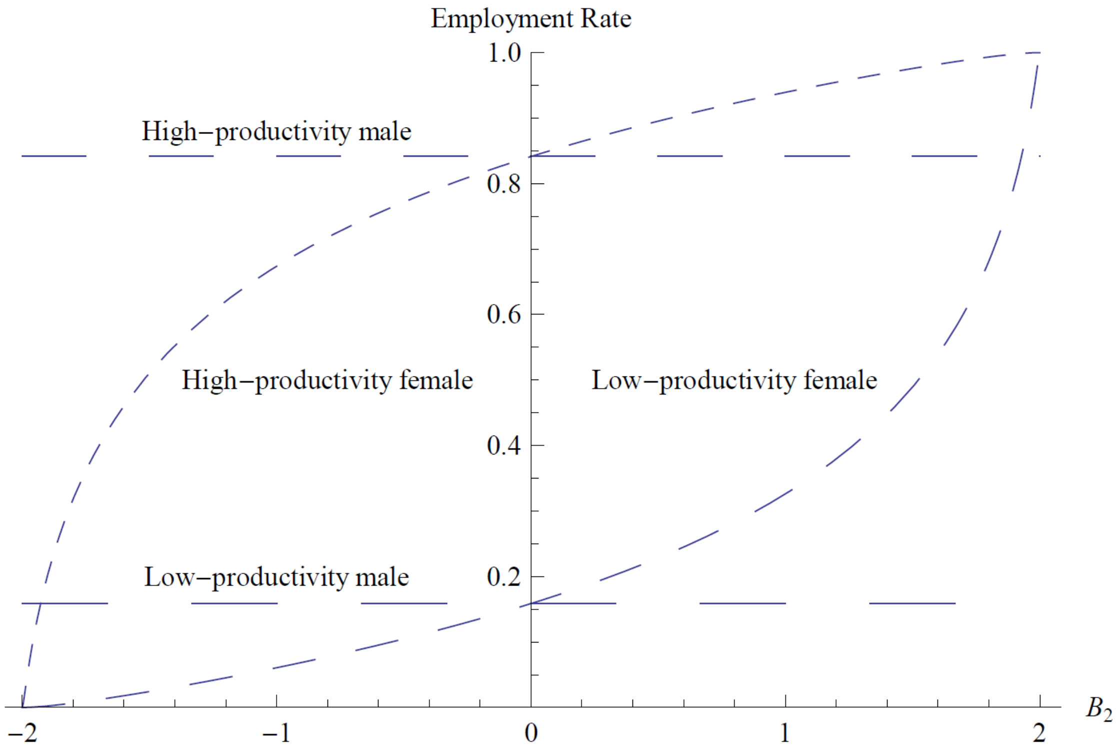
Proposition 2. *With top-down preferences, employment rates among low-ability candidates are strictly increasing in B_2. That is, low-ability candidates are always better off when they can offer employers a privately valued attribute. Alternatively, employment rates among high-productivity candidates are not monotonic in B_2. That is, there exists some $B_2 < 0$ for which the high-productivity candidate is strictly better off than he would be under a regime in which B_2 is large and positive. In a sequential hiring game, the early decision maker has enough influence on the candidate's prospect that the high-productivity candidate would prefer even mild discrimination in later rounds to having agents in later rounds offer strong favor.*

In Figure 2.3 we plot the expected value to the firm of a candidate with and without the influence of Agent 1 across B_2.[12] Not surprisingly, the firm values Agent 1's screen, which is evident in the higher firm values across B_2—Agent 1's screen better enables the hiring of "good" candidates. However, what is more interesting about the role of Agent 1 in the hiring game is the asymmetry introduced into the expected outcomes across B_2. In the absence of Agent 1, the

[12] We normalize to one the expected value to the firm when Agent 2 is naive and there are no private values, $B_1 = B_2 = 0$.

FIGURE 2.2. Employment Probabilities With a Naive Agent 2

Panel A: No screening provided by Agent 1



Panel B: Agent 1 screens candidates prior to Agent 2

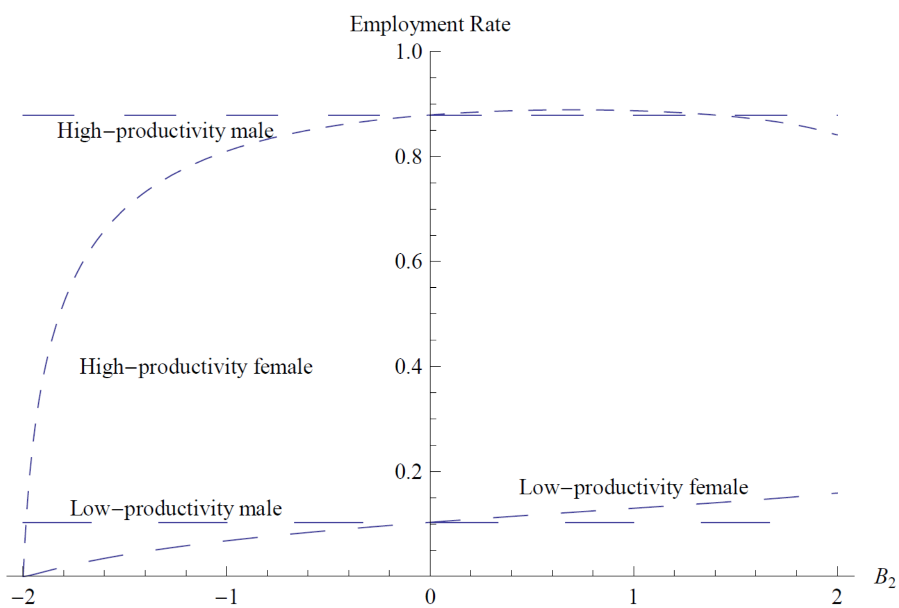
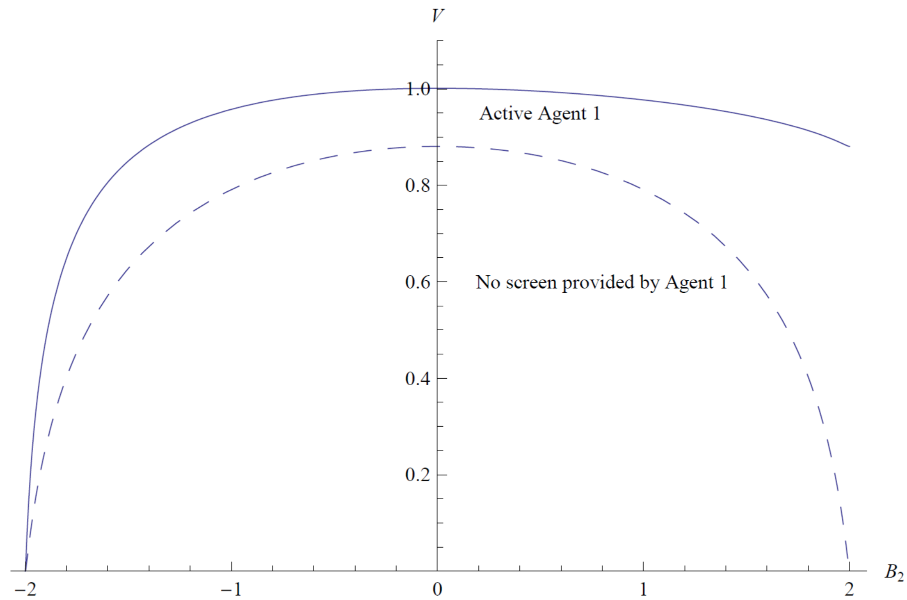


FIGURE 2.3. Firm Value With a Naive Agent 2



expected costs to the firm associated with Agent 2 following his private interest are symmetric around $B_2 = 0$. However, when taking an active role in the hiring, Agent 1 is less effective at offsetting Agent 2's inclination to reject candidates (when $B_2 < 0$) than to hire candidates (when $B_2 > 0$), which introduces an asymmetry in firm value. Thus, given the ability of Agent 1 to unilaterally reject, the expected costs to the firm are higher with top-down discrimination (i.e., for $B_2 < 0$) than with top-down favoritism (i.e., for $B_2 > 0$).[13]

Extensions

Having modeled the direct outcomes of the hiring game, we consider two simple extensions.

Subsequent promotion games

As $B_2 \neq 0$ induces patterns of hiring that are specific to productivity-by-gender pools of candidates, in any subsequent period, average (within-firm) productivity levels will vary by gender. Even in the absence of private values playing a direct role in promotion decisions,

[13] In the limit, as Agent 2's private values decrease, Agent 2 rejects all candidates with the private attribute, regardless of whether Agent 1 is present. In such cases, the expected value to the firm collapses to $V_0 = 0$.

promotion outcomes can be shown to depend on B_2.[14] For example, if $B_2 > 0$ at the hiring decision, the average female in the firm will be of lower productivity than the average male. Assuming that subsequent decision makers will perceive this difference in productivity, this disparity implies that females will suffer lower promotion probabilities within firms. While the implication of heterogeneous productivity in promotion games has been considered in the literature (Bjerk, 2008), we offer a source of heterogeneity—one driven, somewhat surprisingly, by favoritsm.

Performance pay

We next allow for $\tau_1 \leq \tau_2$ in order to consider the firm having taken steps to align the incentives differently across the internal hierarchy. In Figure 2.4 we show the optimal threshold levels for each agent across B_2 for a range of $\tau_2 \in [.5, 1)$, adjusting τ_1 accordingly, such that $\tau_1 = 1 - \tau_2$. For comparison with the baseline model, the solid lines indicate the $\hat{s}_1^\star$ and $\hat{s}_2^\star$ chosen when $\tau_1 = \tau_2 = 0.5$. Clearly, as τ_2 becomes increasingly large, any bias introduced in $\hat{s}_2^\star$ through $B_2 \neq 0$ (either discrimination or favoritism) is mitigated as Agent 2 cares more about the firm's value relative to his own private value as τ_2 increases. This is seen in the flattening of $\hat{s}_2^\star$ in B_2 in Figure 2.4. Importantly, the corresponding flattening of Agent 1's optimal $\hat{s}_1^\star$ in B_2 is entirely in response to B_2's influence on $\hat{s}_2^\star$. That is to say, because we have assumed $B_1 = 0$, any $\tau_1 > 0$ achieves unbiased decisions from Agent 1.[15]

In Figures 2.5 and 2.6 we plot the employment rates for good and bad workers respectively. As expected, increasing τ_2 works to offset biases arising from either $B_2 < 0$ or $B_2 > 0$, and allows for a larger range of these private values over which $\hat{s}_2$ does not collapse to either "always hire" or "never hire" rules.

The Role of Agent 1's Private Value

As one last consideration before generalizing to both agents valuing the candidate's non-productive attribute, note the asymmetry in Agent 1's ability to mitigate Agent 2's biases—when

[14] Of course, if the potential promotion of those with the privately valued attribute continue to be subject to the bias that occurred in the hiring process, outcomes will be affected. In fact, in such a setting, our "hiring" game can itself be recast as a promotion game of sorts.

[15] While we do not devote space to $\tau_1 \geq \tau_2$, these scenarios behave as expected. In the limit, where $\tau_2 = 0$, Agent 2 collapses to never hiring members of the non-preferred group for any $B_2 < 0$ and always hiring members of the preferred group for $B_2 > 0$.

FIGURE 2.4. Reservation Signals Across τ_2 With a Naive Agent 2

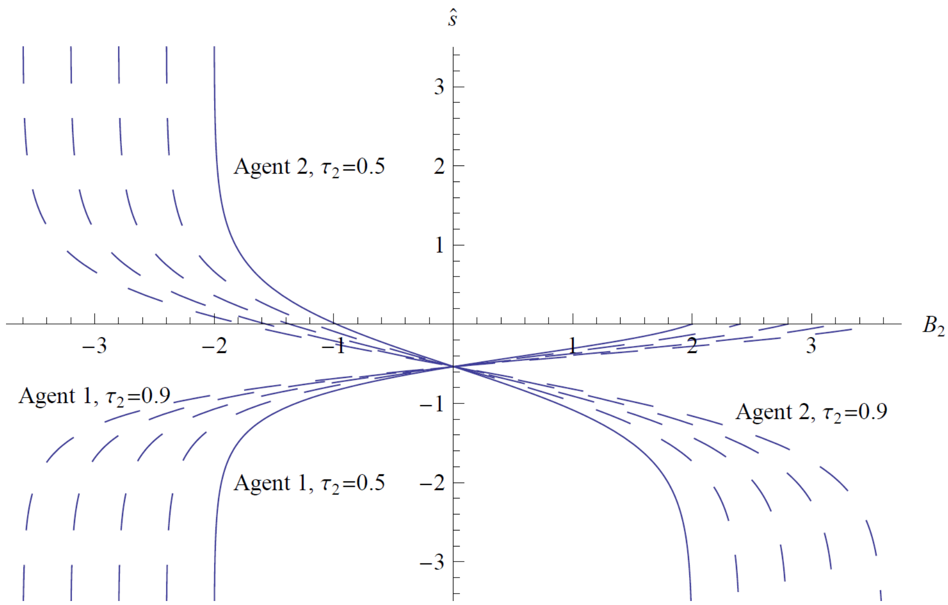


FIGURE 2.5. Employment Rates for "Good" Workers Across τ_2 With a Naive Agent 2

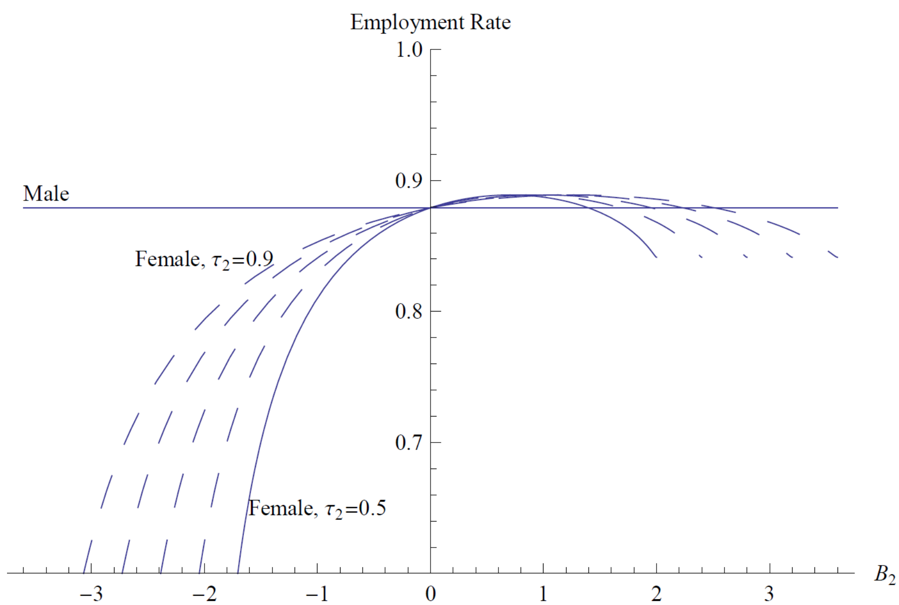
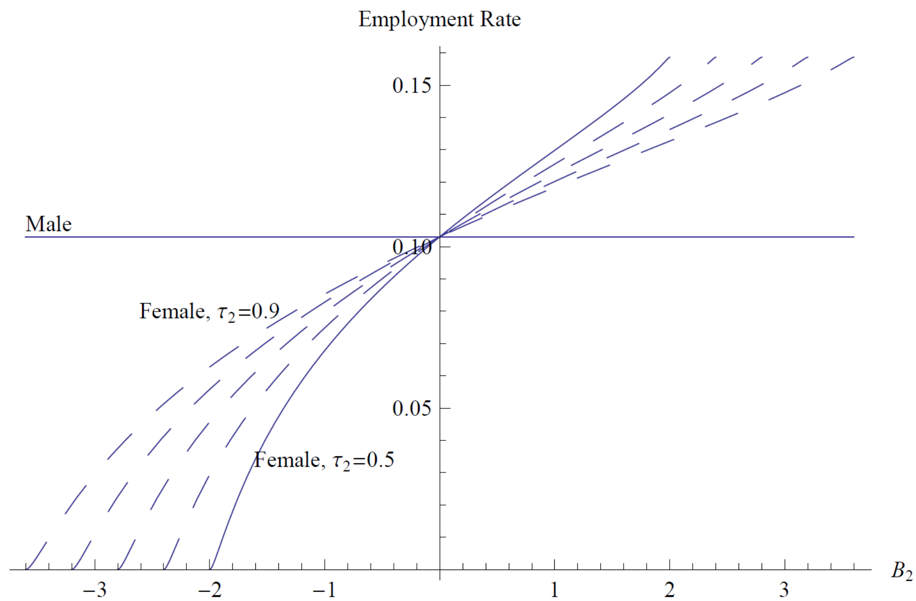


FIGURE 2.6. Employment Rates for "Bad" Workers Across τ_2 With and a Naive Agent 2



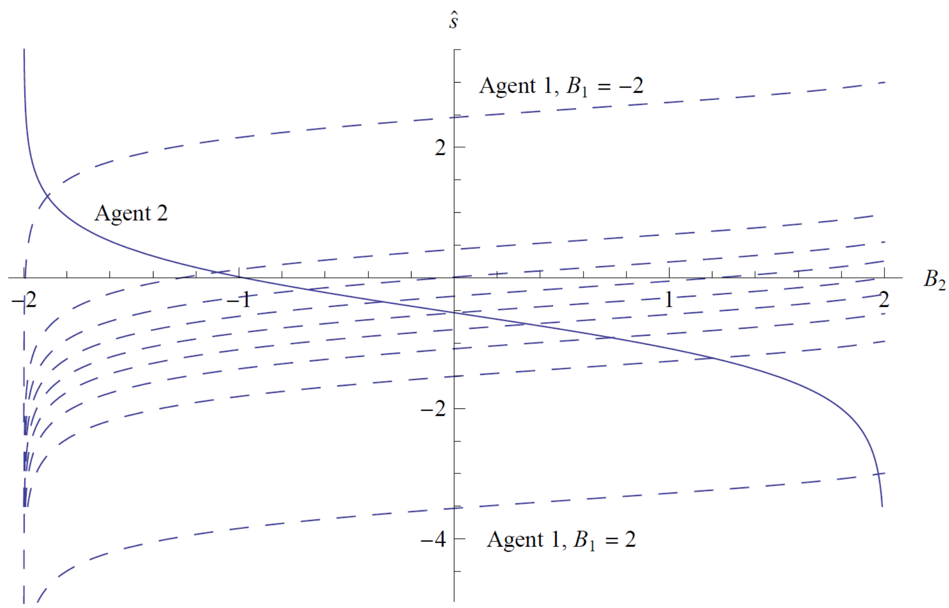
Agent 1 foresees Agent 2's bias, Agent 1 plays a corrective role. Yet, a naive Agent 2 plays no such role when Agent 1 exercises favoritism or discrimination. In this way, our model reverts to the Becker (1957) intuition—Agent 2 simply facilitates a second signal of productivity and acts unbiasedly.

Proposition 3. *For a given private value, $W < 0$, the candidate would prefer to be subjected to a regime where $\{B_1, B_2\} = \{0, W\}$ than to a regime where $\{B_1, B_2\} = \{W, 0\}$. That is, if the candidate is to be discriminated against somewhere, she prefers discrimination to fall late in the sequence. Alternatively, for a given private value, $W > 0$, the candidate would prefer to be subjected to a regime where $\{B_1, B_2\} = \{W, 0\}$ than to a regime where $\{B_1, B_2\} = \{0, W\}$. That is, favoritism is more beneficial if experienced early in the sequence.*

In Figure 2.7, we allow for $B_1 \neq 0$ and $B_2 \neq 0$, capturing that both agents may value the candidate's non-productive attribute. As before, we plot Agent 2's choice of $\hat{s}_2$, but now with a menu of $\hat{s}_1$ corresponding to values of $B_1 \in (\tau_1 V_b, \tau_1 V_g)$. (As Agent 2 is naive, note that B_1 has no influence on $\hat{s}_2$.) Within the series of plots, Agent 1's decision rule in the strictly "top-down" case (i.e., that corresponding to $B_1 = 0$) can be seen in the solid line.

Figure 2.7 illustrates two results. First, as we have assumed that Agent 2 is not best responding to $\hat{s}_1$ at the margin, we document the expected pattern of behavior, that, for any $B_2 \in (\tau_2 V_b, \tau_2 V_g)$, $\hat{s}_1$ is strictly decreasing in B_1. As Agent 1's private value increases, holding

FIGURE 2.7. Reservation Signals Across B_1 When Agent 2 is Naive



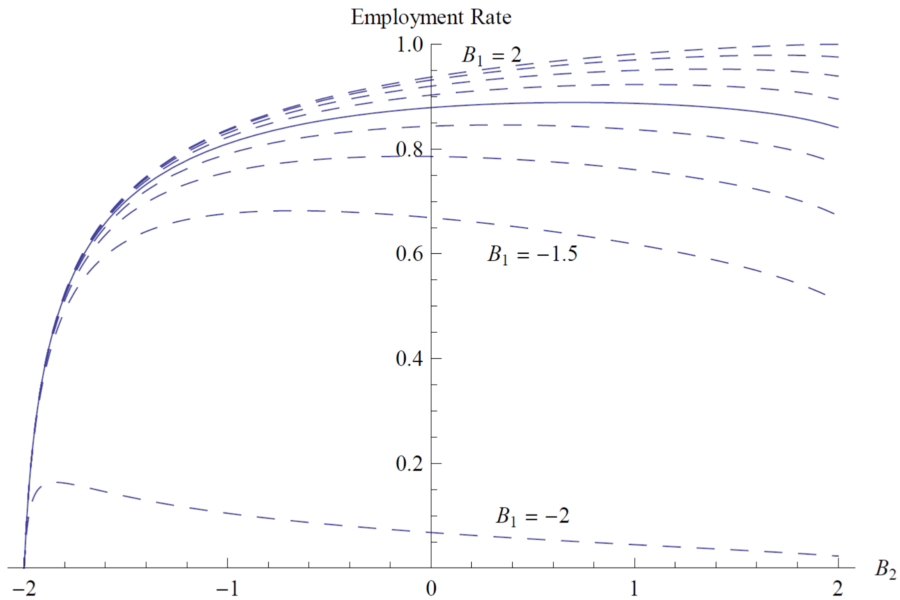
constant Agent 2's private value, Agent 1 is less likely to reject those candidates who have the attribute. The less-obvious takeaway from Figure 2.7, and one we wish to stress, we state as a proposition.

Proposition 4. *For all B_1, $\hat{s}_1^\star$ is strictly increasing in B_2. That is, Agent 1 raises the bar on candidates as Agent 2 is inclined to show less discrimination or more favor.*

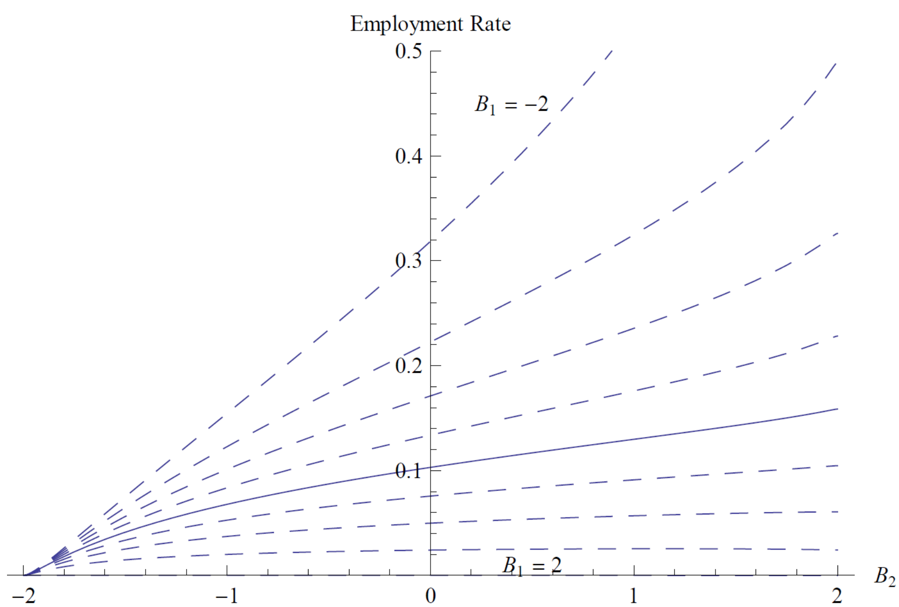
In Figure 2.8 we plot the *ex post* rates of employment for "good" and "bad" female candidates, assuming that female is the private attribute around which the agents are potentially optimizing. As in Panel B of Figure 2.2, Figure 2.8 again captures that employment outcomes are sensitive to B_2, not only as a direct result of Agent 2's private value, but also indirectly through Agent 1's best response to $B_2 \neq 0$. Namely, employment rates among "good" female candidates eventually decline in B_2, reflecting Agent 1's ability to force the rejection of a particular candidate in response to a high B_2. As Agent 1 is less able to force the hiring of a candidate, employment rates among "bad" female candidates again monotonically increase in B_2. In panels A and B of Figure 2.8, then, we demonstrate that this strong tradeoff remains, across all B_1.

FIGURE 2.8. Rates of Employment Among Preferred Candidates When Agent 2 is Naive

Panel A: High-productivity female candidates



Panel B: Low-productivity female candidates



Proposition 5. *Both high- and low-productivity candidates prefer higher B_1 to lower B_1. That is, in a sequential hiring game when the late decision maker is naive, candidates weakly benefit from early preference as late decision makers provide no offsetting or corrective role.*

When Agent 2 Is Savvy

Agent Behavior

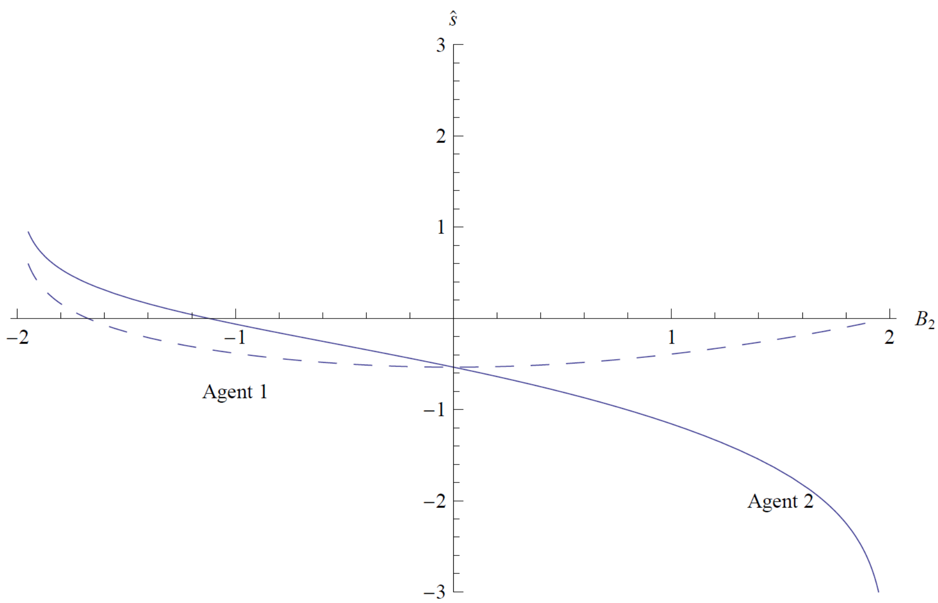
In this section we relax the earlier assumption that Agent 2 is naive (i.e., does not recognize how Agent 1 best responds to $B_2 \neq 0$) and, instead, allow both agents to choose reservation signals while fully anticipating the effect that choice will have on the other agent's choice. While we are granting much more forethought and consideration to Agent 2 than may be evidenced in the field, this case fully bounds the possible scenarios relevant to policy and provides a richer understanding of the potential implications of private values in hiring games.

In Figure 2.9, we return to consider "top down" preferences (i.e., $B_1 = 0$) across a range of $B_2 \in (\tau_2 V_b, \tau_2 V_g)$, but allow Agent 2 to recognize that Agent 1 will adjust $\hat{s}_1$ in response to B_2. First, note that when $B_2 = 0$, both $\hat{s}_1^\star$ and $\hat{s}_2^\star$ are as they were in the case with a naive Agent 2. (This is expected, as one model nests the other when private values are absent.) Likewise, when $B_2 > 0$, the general patterns of behavior are similar to that in the naive-owner case. Yet, where $B_2 < 0$ and Agent 2 correctly anticipates $\hat{s}_1^\star$, both $\hat{s}_1^\star$ and $\hat{s}_2^\star$ behave differently in B_2 (than was the case with naiveté, in Figure 2.1). In particular, Agent 1's reservation signal is no longer monotonically increasing through $B_2 \in (\tau_2 V_b, \tau_2 V_g)$. To contrast, $\hat{s}_1^\star$ is now U-shaped, decreasing in B_2 for all $B_2 < 0$ in this range.

Proposition 6. *With top-down preferences, when Agent 2 is savvy in setting expectations of Agent 1's reservation signal, $\hat{s}_1^\star$ is monotonically decreasing in $B_2 \in (\tau_2 V_b, 0)$. (As when Agent 2 is naive, when Agent 2 is savvy $\hat{s}_1^\star$ is monotonically increasing in $B_2 \in (0, \tau_2 V_g)$.)*

The intuition for this result is again found in Agent 1's inability to fully offset prejudicial bias that arises late in the hiring sequence—while Agent 1 can secure a candidate's rejection, he cannot secure a candidate's hire. When Agent 2 anticipates a higher $\hat{s}_1$, he best responds by increasing $\hat{s}_2^\star$ all the more, which ultimately decreases employment rates among those presenting the privately costly attribute. By increasing $\hat{s}_1^\star$ as Agent 2 is more inclined to discriminate (i.e., as B_2 decreases from zero), Agent 1 is able to induce a lower $\hat{s}_2^\star$ than in the naive case. In essence, where Agent 2 is naive and Agent 1 then has no ability to influence Agent 2's

FIGURE 2.9. Optimal Reservation Signals with a Savvy Agent 2



decision, his decision rule was motivated solely by the potential to offset Agent 2's bias at the margin. Now, where Agent 2 is aware that $\hat{s}_1$ responds to B_2, Agent 1's choice of $\hat{s}_1$ influences $\hat{s}_2^\star$ at the margin. By raising his standard on candidates in the first period, Agent 1 lowers the marginal benefit to Agent 2 increasing $\hat{s}_2^\star$ in the second period, thereby allowing the firm to better exploit the gains available through the second signal of productivity. We learn by this that prejudicial bias introduced late in a sequential hiring game can motivate what looks like a prejudicial bias in earlier rounds; a preemptive bias-correction, of a sort. In this way taste-based discrimination introduced late in a sequence can yield a sort of statistical discrimination earlier in the sequence. However, in this setting, Agent 1 is not responding to a perceived difference in the average productivity of female candidates—as would be the case in standard models of statistical discrimination—but in recognizing that subsequent decision makers will lean away from an unbiased assessment of productivity, treats female candidates differently as a corrective action.

Implications for Employment and Firm Value

In Panel A of Figure 2.10 we again plot employment rates—the patterns are remarkably similar to those in the naive case. With Agent 2 now savvy, both high and low-productivity females are more likely to be hired for $B_2 > 0$ and less likely to be hired for $B_2 < 0$.

In Panel B of Figure 2.10 we plot the expected value to the firm of considering a candidate for the savvy and naive cases. While the firm's expected value is invariant to the assumption of naiveté when $B_2 = 0$, slight differences emerge at other values of B_2. In general, the firm suffers more from Agent 2's privately motivated decisions when Agent 2 is savvy; Agent 1 offers less of a corrective influence in such cases. The exception to this rule is for extreme discrimination (i.e., B_2 approaching V_b), where Agent 1's higher standard enables the firm to escape Agent 2's "always reject" regime.

The Role of Agent 1's Private Value

In Panel A of Figure 2.11, for various values of B_1, we plot the rates at which high-productivity female candidates are hired across B_2. (Recall that we use the hiring of female candidates as a placeholder of sorts in the figures, which more-broadly apply to any observable non-productive attribute for which there may be private consideration.) The bold line captures the parameterization already represented in Figure 2.10. Around this line, however, we see the interesting asymmetry of employment rates. For example, where B_2 is large and negative and Agent 2 is increasingly inclined toward adopting a "never hire" position, Agent 1 has no ability to influence employment regardless of his inclination to do so (i.e., for any B_1). Thus, for all B_1, employment rates converge to zero as B_2 decreases to $\tau_2 V_b$. As B_2 increases from $\tau_2 V_b$, employment rates fan out across B_1, with rates increasing faster in B_2 for higher values of B_1. This, again, reflects Agent 1's ability to "force" rejections (e.g., when B_1 is low), while being quite unable to force hires—even in the limit (as B_1 increases to $\tau_1 V_g$), employment is still very much dependent on Agent 2's private value (B_2).

In Panel B of Figure 2.11 we plot the expected value to the firm of a female candidate. That the expected value is highest when $B_1 = B_2 = 0$ again reflects that any privately motivated interest, in either agent, is costly to the firm. Moreover, it is interesting to note that for all B_2, firm value is maximized when $B_1 = 0$. That is, in the sequential hiring game, the full value

FIGURE 2.10. Employment Probabilities and Firm Value With a Savvy Agent 2

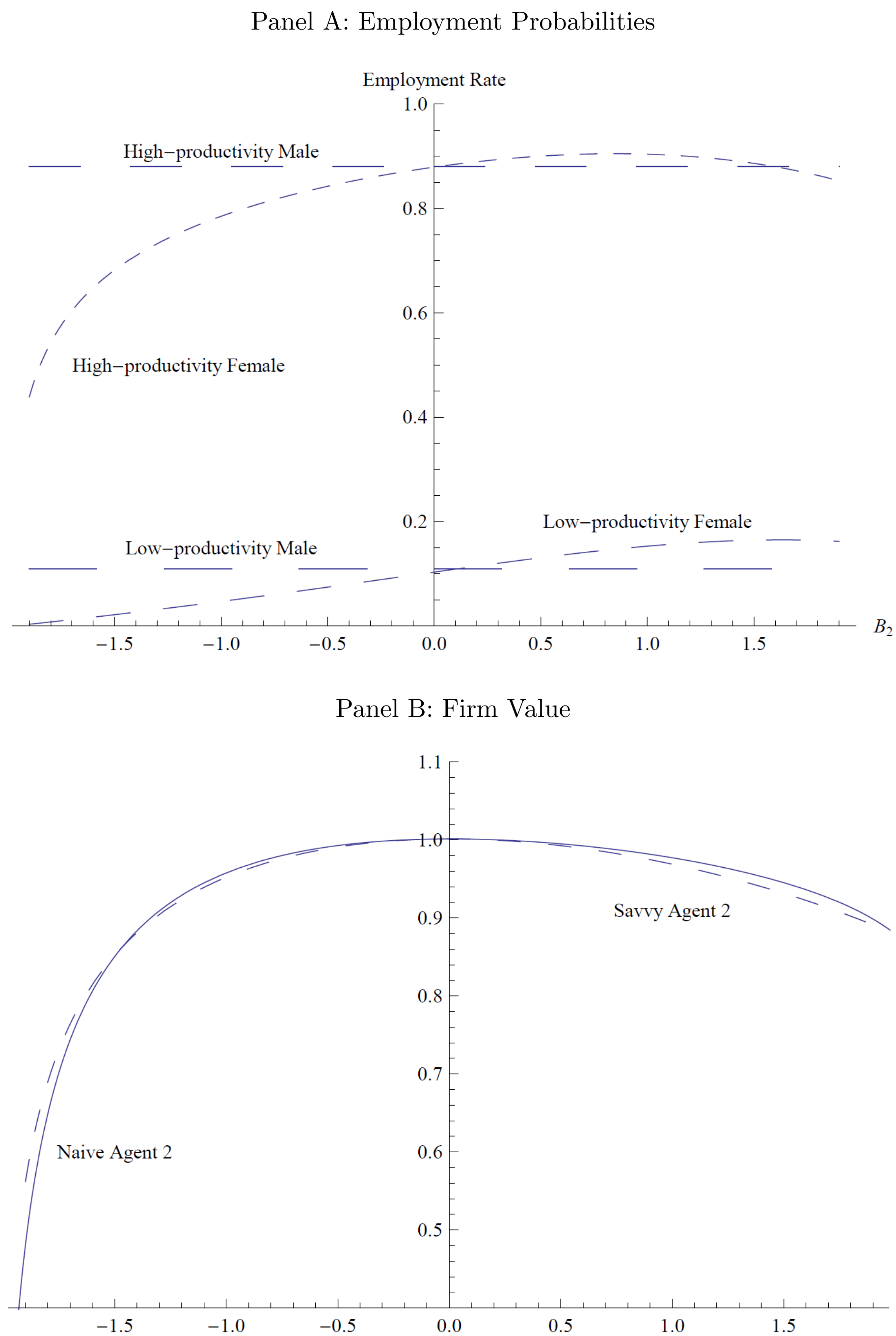
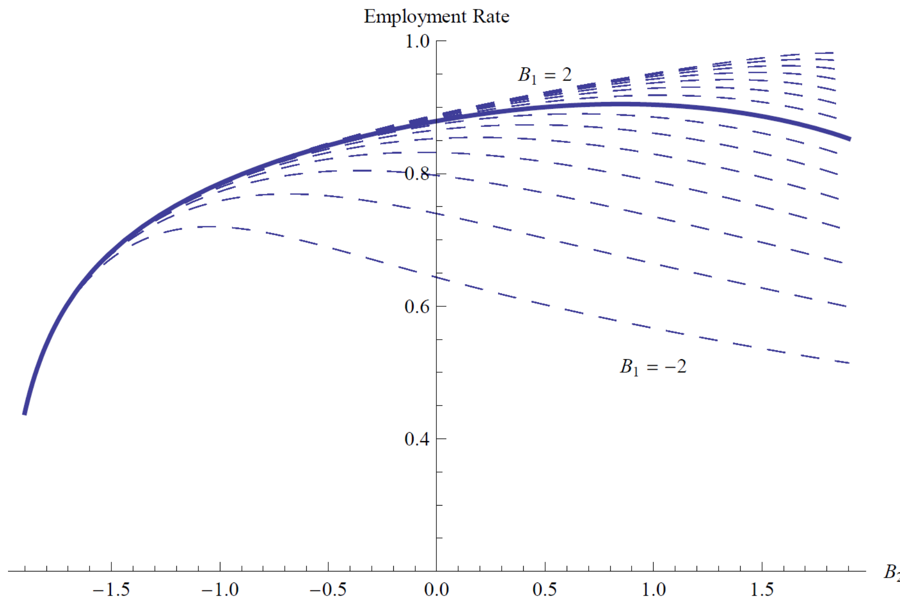
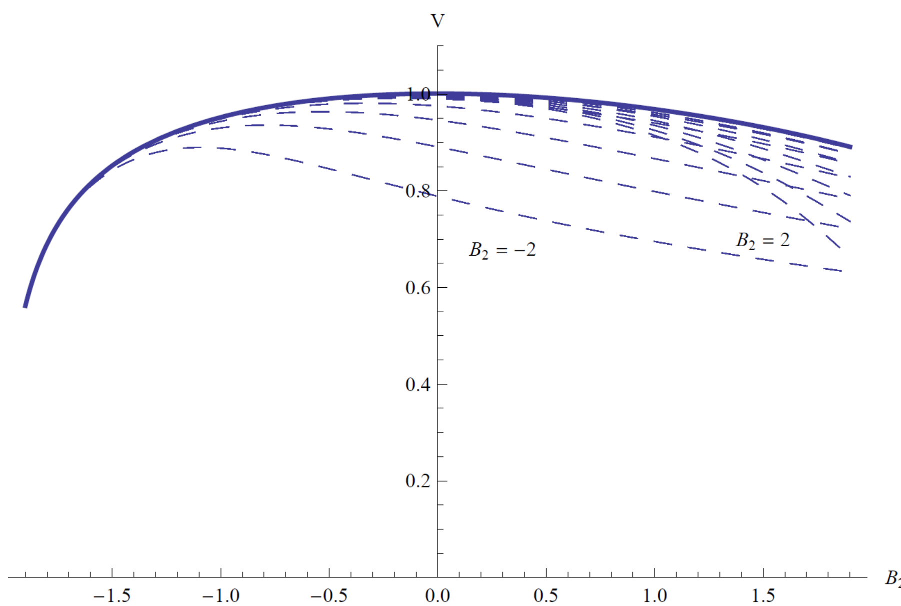


FIGURE 2.11. Employment Probabilities and Firm Value When Agent 2 Is Savvy - Across β_1

Panel A: Employment probabilities among "good" female candidates



Panel B: Expected firm value in assessing a privately valued candidate



to having multiple signals drawn and evaluated is only exploited when the first agent is free from bias. Any departure from this not only costs the firm directly (through Agent 1 choosing a standard that depends on B_1), but indirectly costs the firm through Agent 1's influence on Agent 2's decision (even when $B_2 = 0$).

The timing of preference—whether introduced with Agent 1 or Agent 2—yields striking differences in agents' optimal thresholds. In Figure 2.12, we impose bottom-up preferences (i.e, $B_2 = 0$) and plot agents' optimal thresholds (Panel A) and associated employment probabilities (Panel B) across B_1. Most notable, with bottom-up preferences, Agent 2's optimal threshold is monotonically increasing in B_1. This is different from the patterns evident with "top-down" preferences (recall Figure 2.9), where the agent without private preference appears to "buy" more-lenient treatment from the agent who finds the candidate's non-productive attribute privately costly.

The importance of the timing of bias is also seen in Panel B of Figure 2.12, where we plot associated employment probabilities by productivity. With discrimination, the timing of the introduction of private values is of little consequence to employment; either agent can unilaterally dismiss candidates. As no single agent can unilaterally hire a candidate, preference for a candidate's non-productive attribute yields different patterns of behaviour. With bottom-up preferences, both good and bad female candidates are more likely to be hired than male candidates, for all B_1. This contrasts with top-down preferences (see Panel A of Figure 2.10) where strong preference on the part of Agent 2 ultimately leaves good female candidates less likely to be hired.

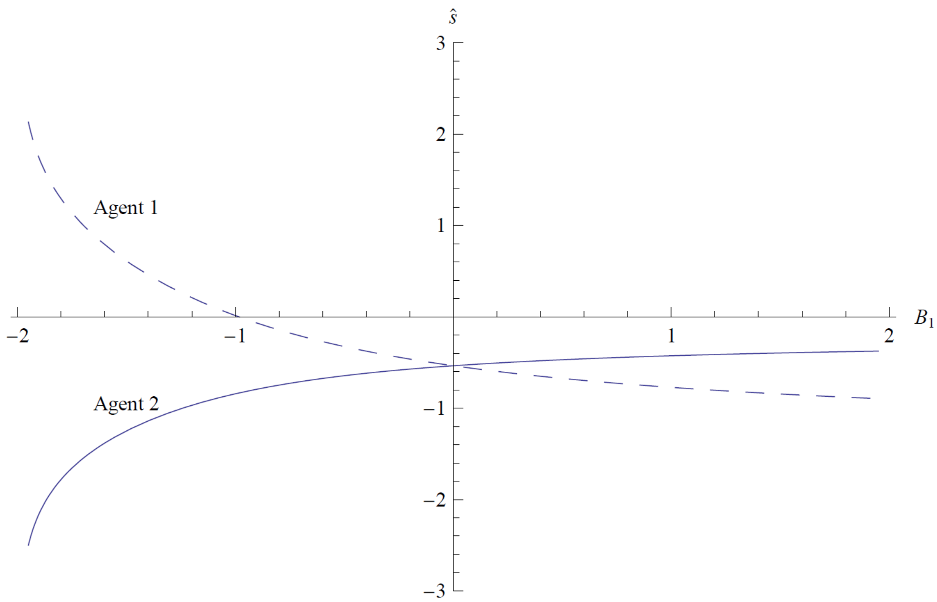
Can Agent 2 Incentivize Agent 1's Cooperation?

Given the similarity in employment outcomes when we assume Agent 2 is savvy, we forgo additional discussion of subsequent hiring and promotion games and the implications of performance pay in this environment. Yet, unique to the environment in which Agent 2 fully anticipates Agent 1's best response to $B_2 \neq 0$ (which, loosely speaking, is to take corrective action and mitigate Agent 2 acting on his private valuations), it is interesting to consider the potential for a transfer, from Agent 2 to Agent 1, to incentivize Agent 1's cooperation.[16]

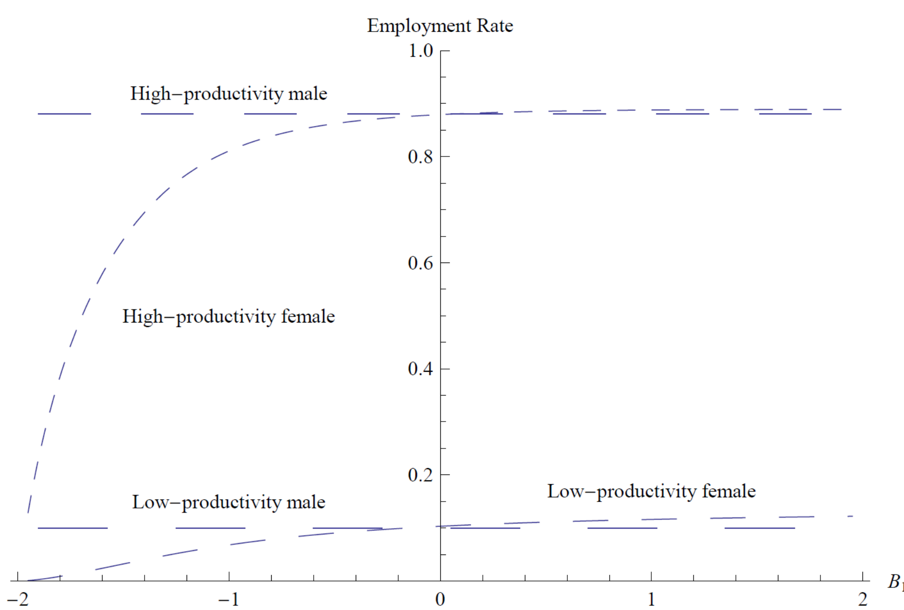
[16]We do not discuss the feasibility of such a payment in the "naive" case, as Agent 2 recognizing the need to "correct" Agent 1's action seems a prerequisite to explaining the use and effect of such payments.

FIGURE 2.12. Optimal Reservation Signals and Employment Probabilities

Panel A: Optimal Reservation Signals



Panel B: Employment Probabilities



Here we consider one important extension to the model—a potential transfer, from the firm (although at Agent 2's choosing) to Agent 1, attached to the hiring of a candidate presenting a particular non-productive attribute. We ask, then, whether there are private values $\{B_1, B_2\}$ for which Agent 2 will choose to reward Agent 1 for hiring such a candidate.[17]

Such practice appears in academic markets, for example, where payments would typically be made, by college-level administrators to departments, conditional on hiring a candidate who presents with a non-productive attribute, such as a minority race of gender. We parameterize this payment with ρ, through which we allow Agent 2 to transfer $\rho > 0$ from the firm to Agent 1, conditional on hiring a candidate with a particular (non-productive but verifiable) attribute. Agent 2's objective can therefore be written as,

$$\begin{aligned}
\operatorname*{Max}_{\hat{s}_2,\rho} V_2(\hat{s}_2) \quad = \quad & \alpha[F_g(\mathbb{E}_2[\hat{s}_1]) + (1 - F_g(\mathbb{E}_2[\hat{s}_1]))F_g(\hat{s}_2)]\tau_2 V_0 \\
& +\alpha(1 - F_g(\mathbb{E}_2[\hat{s}_1])(1 - F_g(\hat{s}_2))(\tau_2(V_g - \rho) + B_2) \\
& +(1-\alpha)[F_b(\mathbb{E}_2[\hat{s}_1]) + (1 - F_b(\mathbb{E}_2[\hat{s}_1])F_b(\hat{s}_2)]\tau_2 V_0 \\
& +(1-\alpha)(1 - F_b(\mathbb{E}_2[\hat{s}_1]))(1 - F_b(\hat{s}_2))(\tau_2(V_b - \rho) + B_2),
\end{aligned} \tag{2.8}$$

where the payment reflects a reduction in firm value by the amount ρ upon hiring. Similarly, as Agent 1 receives ρ, his objective equation becomes,

$$\begin{aligned}
\operatorname*{Max}_{\hat{s}_1} V_1(\hat{s}_1) \quad = \quad & \alpha[F_g(\hat{s}_1) + (1 - F_g(\hat{s}_1))F_g(R_2)]\tau_1 V_0 \\
& +\alpha(1 - F_g(\hat{s}_1))(1 - F_g(R_2))(\tau_1(V_g - \rho) + B_1 + \rho) \\
& +(1-\alpha)[F_b(\hat{s}_1) + (1 - F_b(\hat{s}_1))F_b(R_2)]\tau_1 V_0 \\
& +(1-\alpha)(1 - F_b(\hat{s}_1))(1 - F_b(R_2))(\tau_1(V_b - \rho) + B_1 + \rho).
\end{aligned} \tag{2.9}$$

In giving away part of the firm, the private cost to Agent 2 is merely his share of the direct reduction in firm value, $\tau_2\rho$. On this margin, then, any increase in ρ is less costly to Agent 2 when τ_2 is small. Regardless, however, Agent 2 benefits by any such payment only to the extent that it

[17] US labor law forbids deductions from employee pay without serious violations of workplace rules. As such, we do not consider whether there are values for which Agent 2 would tax Agent 1 for hiring a candidate with a particular non-productive attribute. Regardless, the sequential nature of the hiring process limits Agent 2's ability to require payment from Agent 1 for hiring a candidate, as Agent 1 can always avoid such penalties by raising the required standard for hire. Agent 1 still solves the first-order condition for $\hat{s}_1$, of course, so while Agent 1 will not collapse to an "always reject" position immediately, in the limit, $\hat{s}_1^\star$ approaches "always reject."

moves Agent 1 in his preferred direction. Since Agent 1 also pays a share of the cost of $\rho > 0$ (in terms of firm value, $\tau_1\rho$), awarding $\rho > 0$ to Agent 1 is more powerful when τ_1 is small. Thus, only for small τ_1 and τ_2 can Agent 2 benefit from a non-zero transfer of $\rho > 0$ from the firm to Agent 1.

In many cases, however, Agent 2 finds $\rho^\star = 0$ to be optimal. This implies that the additional dollar that would be used to influence $\hat{s}_1^\star$ generates less than a dollar's worth of return in noise reduction and increased probability a candidate will be hired. Intuitively, Agent 2 is most likely to choose a non-zero ρ in cases where B_2 is large. In the extreme case, where $B_2 \to \tau_2 V_g$, we have shown (in Figure 2.9) that Agent 1 acts as though he were the only screen ($\hat{s}_1^\star = 0$) while Agent 2 collapses to always hiring candidates that make it through the first screen. This leads to a significant increase in the number of low-productivity workers hired relative to the number of high-productivity workers hired and limits the payoffs to all parties. By choosing $\rho > 0 > B_2$, Agent 2 incentivizes Agent 1 to lower his chosen threshold, bringing $\hat{s}_1^\star$ more in line with $\hat{s}_2^\star$ and increasing the average productivity of workers hired.

Conclusion

In this paper we consider a firm's hiring process, with agents of the firm each drawing a signal of a candidate's productivity and choosing to either reject or forward the candidate based on that signal (or make the hire, if last in the sequence). Into this setting we introduce that agents may also have private costs or benefits associated with some non-productive personal attribute of the candidate. The implications are interesting and non-trivial.

We show that private values introduced in one stage of such a game are evident not only in the actions of the agent harboring those private motivations, but also among agents in other stages of the game, even if they neither benefit nor suffer privately with the outcome of the game. In particular, where preference *for* a personal attribute is introduced late in the sequence, earlier decision makers partially offset this preference by raising the standard they impose on a candidate with that personal attribute. From the firm's perspective, this moves toward first best and we therefore characterize this potential as partially corrective. In the typical "up-or-out" hiring environment, where earlier decision makers have much more sway in rejecting candidates than in hiring candidates, the potential response among earlier decision makers who anticipate subsequent favorable treatment still has the potential to subject candidates who are "preferred," on average, to lower odds of employment than they would have experienced had their private attribute not been valued or observable.

In closing, we note four interesting implications, each of which may motivate additional exploration. First, where a single decision maker discriminates on taste, the average productivity among the "preferred" group decreases. However, as early movers in a sequential decision can take positions offsetting top-down preferences, average *ex post* productivity falls off more slowly among those who are "preferred" *a priori*. For example, with top-down preferences, early decision makers who anticipate excessively favorable treatment of female candidates in subsequent evaluations best respond by increasing the standards they impose on female candidates, which implies that later decision makers will be considering female candidates who are, on average, of higher quality (i.e., able to have cleared the higher standards imposed in early rounds). Therefore, while fewer female candidates advance in the sequence, the average productivity of those who do advance for final consideration is higher. As such, this may leave later decision makers increasingly misinformed of underlying female productivity, thereby reinforcing or strengthening prior beliefs among those in leadership positions. Overall, the influence of late-arriving preference for female candidates will change the mix of low- and high-productivity female employees such that average productivity falls among female employees. This, we presume, also introduces a source of downward pressure on female wages and thereby contributes to the persistence of male-female wage gaps.

Second, in a setting where late decision makers are savvy enough to anticipate the best responses of early decision makers, early-moving agents, who themselves may be uninclined to discriminate, will *raise* the bar on candidates against whom leadership is inclined to discriminate. Average productivity of female candidates is therefore higher coming out of early stages, thereby moving subsequent priors away from "reject" and toward "accept." Interestingly, where standard models of taste-based discrimination yield heterogeneity in *ex post* productivity by gender and standard models of statistical discrimination yield homogeneity in *ex post* productivity, the sequence of decision making in our setting allows for taste-based discrimination to exist, yet, due to the corrective action of an earlier agent of the firm, *not* be evidenced in *ex post* heterogeneity in productivity by gender.

Third, the model offers interesting implications in light of existing evidence that resumes with African-American-sounding names receive fewer call backs (Bertrand and Mullainathan, 2004). While such an empirical regularity is consistent with either a single decision maker statistically discriminating or a single decision maker exercising a kind of taste-based discrimination, it is also consistent with the actions of the first of multiple decision makers in a regime where subsequent decision makers are expected to show preference *for* African-American candidates. (We assume that call-back decisions are made by initial screeners and not by those who will ultimately make the hire.) Of course, policy prescriptions across these potential mechanisms will differ significantly.

Finally, note that the model we present implies that if preferences for the private attribute are of the top-down variety we describe, we should be concerned that even in regimes where women and racial minorities are valued by leadership, such candidates can be harmed by revealing their identities early if initial screeners merely value those attributes less than leadership. Candidates will also experience tension, insofar as they do benefit from eventually revealing their identities. (In the model, they would choose to identify strictly between Agent 1 and Agent 2.) "Blind" assessments should arguably be considered in this context, as outcomes are certainly not neutral with respect to the information provided to reviewers. For example, in regimes where preferences for female recruitment are not uniformly held across the firm's hierarchy, pro-minority leadership meets with more success by incorporating blind-recruitment tools in early assessments of job candidates.

CHAPTER III

INMATE RESPONSES TO INCENTIVES FOR GOOD BEHAVIOR

This chapter is a component part of co-authored work with Glen R. Waddell and Benjamin Hansen in which I am a full participant.

Introduction

America has a prison problem. In 2008, there were 2.3 million people incarcerated in the United States at an estimated annual cost of 75 billion dollars.[1] Rapid growth in the imprisoned population has also led to significant overcrowding, with recent estimates suggesting that current populations are upwards of 108 percent of capacity.[2] Already, the United States incarcerates more people and a higher percentage of its population than any other country.[3] In fact, Oregon, Vermont, Michigan, Connecticut, and Delaware currently spend more on their prison systems than on higher education with nationwide prison spending increasing six-times faster than spending on higher education over the past 23 years.[4]

While the costs of mass incarceration have recently attracted public attention, a significant literature has suggested crimes prevented through incarcerating prisoners justifies the cost. Overall, it appears that the marginal benefit exceeds the marginal cost for the average prisoner in many settings (Levitt, 1996; Owens, 2009; Buonanno and Raphael, 2013). However, more recent evidence suggests the returns to incarcerating marginal prisoners in the United States may have declined to inefficient levels (Johnson and Raphael, 2012).

One of the principal drivers of the increased incarceration rates have been increased sentence lengths served by prisoners (Raphael and Stoll, 2013). Many factors drove this increase. One significant shift was the adoption of truth-in-sentencing reforms and mandatory minimum punishments. Upon adopting truth-in-sentencing reforms, many states replaced parole boards with

[1] "The High Budgetary Cost of Incarceration," Center for Economic and Policy Research (June 2010)

[2] "Prison Population Rates per 100,000 of the national population," http://www.prisonstudies.org/info/worldbrief/wpb-stats.php (Jan 2013)

[3] Ibid

[4] "New High in Prison Numbers," The Washington Post (Feb 2008). "When will the U.S. stop mass incarceration?" CNN (July 2012).

"good time", which allowed some prisoners to earn a pre-determined fraction of their sentence off based on their behavior. At the same time, states which retained parole boards often reduced or eliminated the discretion of the parole board, with parole in essence becoming a mandatory event which happened after the prisoner had served a pre-determined portion of their sentence with good behavior. Currently, 32 states offer some form of "good time," where prisoners' sentences are deterministically reduced as long as the prisoner avoids misconduct citations (Lawrence and Lyons, 2011). The shifts in policy towards good time have been largely justified with claims that they will lower the costs of incarceration, while also having the potential to contribute to reductions in the criminogenic effects of incarceration.

The effectiveness of these within-prison deterrence effects have long been assumed by policymakers and voters with good time policies standing alongside only community corrections as correctional policies that have received broad support from the public (Skovron, Scott, and Cullen, 1988). As Larkin (2013) suggests, "Good-time laws never have been as politically volatile with the electorate, and have never generated the same visceral, adverse reaction from the public as have the parole laws ... Perhaps that is because the availability of good-time credit was universally accepted as a necessary tool for wardens to prevent institutions from becoming a Hobbesian state of nature." Despite the strong public support for good time policies, there is very little empirical evidence about the relationship between good-time policies and prisoner misconduct rates.[5] Whether sentence-reduction policies are effective in actuality depends largely on the deterability of inmates (Drago, Galbiati, and Vertova, 2009; Blumstein, Cohen, and Nagin, 1978; Abrams, 2012; Hansen, Forthcoming). We seek to understand how individuals, who incidentally were not deterred from committing crimes based on existing enforcement levels and punishments, respond to the deterrent incentives of assessment cycles.

Shifting to more-generous "good time" has recently attracted media coverage, as the role of earned time has intersected with the nationwide problem of mass-incarceration and prison overcrowding. Indeed, more-generous good time could theoretically improve prisoner behavior while incarcerated and thereby reduce costs. With movements to increase good time available at the federal level (e.g., The Barber Amendment would double the federal good time earned),

[5]More research exists in the consideration of prison-administrators' perceptions of good-time policies. In general, surveyed prison officials feel that good-time policies are important to maintaining control of prisons (Ross and Barker, 1986). Morris, Longmire, Buffington-Vollum, and Vollum (2010) finds that inmates sentenced to longer mandatory prison terms are less likely to commit violent misconducts.

Oregon's recent good-time modifications, driven by budgetary considerations, provide a unique quasi-experiment to assess whether the incentives offered by good time shift prisoner behavior while they are still behind bars. Between the 2009 and 2013, Oregon shifted the amount of good time prisoners could earn on four occasions, alternating between more- and less-generous good time. We examine unique administrative records on prisoner behavior and misconducts over this window. In addition, good time was awarded over six-month intervals, thereby enabling both the shifts in good-time generosity and potential change in prisoner behaviour over the assessment cycles to determine whether inmates are responsive to those incentives for good behavior.

The remainder of the paper proceeds as follows. In Section 3.2, we detail the policy variation we exploit for identification, as well as the manner in which prisoners can earn time off their sentence. In Section 3.3, we discuss the data and methodology, presenting our main results in Section 3.4. We consider the review cycles themselves in Section 3.5, and offer concluding remarks in Section 3.6.

Background

Federal and state sentencing practices have experienced fundamental shift toward truth in sentencing over the last 20 years. While many states—Oregon among them—have abandoned parole boards altogether in favor of determinate sentencing, states have exhibited significant variation in the details of the determinant sentencing regimes they employed. Furthermore, determinant sentencing regimes are often adjusted to match political and budgetary demands. For example, truth in sentencing generally implies that convicts serve the sentences assigned to them, but sentence reductions can and are often made available to prisoners in exchange for prescribed good behavior.

When parole was abandoned in Oregon in 1989, the model that replaced it allowed for sentence-length reductions of up to 20 percent.[6] While this is accurately characterized as a reward for good behavior, the sentence reductions have traditionally been framed as a punishment for bad behavior. In fact, prisoners are informed upon entry that they should expect to receive all

[6] A number of states have transitioned away from parole Kuziemko (2013) analyzes the impact of this transition.

available sentence reductions and thereby exit prison at 80 percent of their maximum sentence.[7] While the 20-percent rule stood in place for some time in Oregon, this policy has been changed several times in recent years, largely motivated by budgetary concerns. It is these regime changes we exploit for identification, following several administrative rule changes that increased sentence reductions from 20 to 30 percent for some crimes, later reversed this ruling, only to reinstated the 30-percent rule again for a smaller subset of crimes. In addition, every six months prisoners have an evaluation of their misconducts and any associated losses are determined and are thereafter irrevocable.[8]

In addition to major misconducts, prisoners can lose sentence reductions for failing to attend mandatory programming such as drug counseling or pre-release orientation. In each six-month review, half of the available sentence reductions are based on misconducts while the other half are automatically earned if the prisoner has not missed any of their assigned programming. In practice, prisoners earn the maximum possible good time in 90% of 6 month review cycles. Major misconducts are to blame in approximately 70% of the cases in which full sentence reductions are not earned with programming infractions accounting for the other 30%.[9]

The incentives to behave while in prison may also effect recidivism and future crime by reducing the criminogenic effects of prison. Both Chen and Shapiro (2007) and Drago, Galbiati, and Vertova (2011) find that more-secure prisons with relatively harsh conditions lead to increases in post-release crime. A potential mechanism for this effect is the increased misconducts prisoners experience in prisons with higher security levels. Further evidence suggests that the criminogenic effects of prison lead to significant increases in post-release crime relative to criminals who were not incarcerated (Di Tella and Schargrodsky, 2013; Nieuwbeerta, Nagin, and Blokland, 2009).

The consistent finding that prison time leads to increased future crime has a number of potential explanations including criminal-network development (Bayer, Hjalmarsson, and Pozen,

[7]This type of framing causes the sentence reductions for good behavior to be viewed by inmates as punishments for bad behavior. Bushway and Owens (2013) finds that framing can significantly alter criminal behavior, with perceived punishment severity reducing recidivism.

[8]Sentence reductions are not available to prisoners convicted of certain violent crimes which have mandatory minimum punishments (also referred to as "Measure 11" offenses). Measure 11 offenders still experience behavioral reviews in six-month intervals. In practice Oregon continues to incentivize these prisoners with privileges such as preferred housing, visitation, and other privileges which may be removed following an unfavorable review.

[9]The authors have looked into whether good behavior may be affected by more generous sentence reduction policies but find no evidence that the rate of programming based sentence reduction penalties changes when prisoners are more incentivized to attend.

2009) and the development of norms that favor crime (Trulson, Caudill, Haerle, and DeLisi, 2012). In addition, there is significant evidence suggesting that misconducts while incarcerated are predictive of future crime (Cochran, Mears, Bales, and Stewart, 2012). This implies that reductions in misconduct rates may yield long-term benefits through decreasing criminogenic effects.

In a meta-analysis of 39 studies, Gendreau, Goggin, and Law (1997) finds that both personal characteristics such as risk preferences and situational factors including prison security level could be used to predict misconduct rates. In addition, prison systems often do internal analyses to improve their own ability to predict misconducts. In Oregon, for example, incoming prisoners are assigned a "violence-predictor score" based on the prisoner's age, gender, prior incarcerations, type of crime, aggression level, drug history, and personality disorders (if any). This score is then used to determine the likelihood that the prisoner commits violent misconducts in their first year of incarceration and thereby contributes to determining the appropriate security level for their incarceration. One important element not included in these evaluations is the prisoner's eligibility for parole and/or deterministic-sentence reductions. This omission is noteworthy due to the strong evidence that prisoner's serving sentences without eligibility for parole commit significantly more misconducts than do their parole-eligible peers (Bales and Miller, 2012).

Data and Methods

Data

All data come from the administrative records of the Oregon Department of Corrections, inclusive of prisoner characteristics at admission and high-frequency information about misconducts, activities, and the timing of prisoner assessment and their outcomes.[10] Our sample used for analysis includes all adult-male inmates who committed crimes on or after 1 July 2009 but before 1 July 2013. We observe misconducts for this sample for the portion of sentences served between 1 July 2009 and February 28, 2015. Our first-order interest will be to estimate the effect of the changes to sentence-reduction policy on prisoners' propensities to commit

[10]The information regarding prisoner characteristics at admission include the inmates' age, race, criminal history (number of convictions and types), education, conviction dates, and offense date.

TABLE 3.1. Summary Statistics

	All Prisoners	Group A	Group B	Group C	Group D
Major Misconducts	2.35	4.68	2.01	2.58	2.00
Drug Misconducts	0.13	0.29	0.07	0.34	0.28
Violent Misconducts	0.32	0.67	0.24	0.11	.012
Single-Person Misconducts	0.60	1.31	0.50	0.64	0.51
Multi-Person Misconducts	1.00	2.00	0.90	1.12	0.84
Fraction of Time Earned	0.90	0.84	0.92	0.90	0.91
Fraction Lost for Misconducts	0.07	0.13	0.05	0.07	0.06
Days from Crime to Conviction	210.17	218.15	264.55	211.47	203.09
Total Crime Convictions	1.85	3.36	1.71	1.91	1.66
Violent Crime Convictions	0.34	0.98	0.87	0.25	0.26
Sentence Length	895.60	2,143.30	789.51	868.19	786.83
Age	35.15	34.65	31.32	35.03	35.65
Max Days Served (by 02/28/2015)	591.01	985.06	594.64	614.85	535.62
White	0.75	0.75	0.76	0.76	0.74
Black	0.09	0.09	0.08	0.10	0.09
Hispanic	0.13	0.13	0.13	0.10	0.14
Other Race	0.03	0.03	0.03	0.04	0.03
ACRS Score	0.27	0.23	0.19	0.24	0.30
Recidivists	0.38	0.58	0.24	0.32	0.41
Parole Violators	0.21	0.37	0.14	0.18	0.22
Prisoners	8,549	528	500	2,609	4,912

Notes: Group A includes only prisoners convicted of crimes that made them ineligible for sentence reductions. The All eligible category includes all prisoners not in group A. Group B includes only prisoners convicted of crimes that were eligible for 20-percent sentence reductions regardless of the date the crime was committed. Group C includes prisoners convicted of crimes that were eligible for sentence reductions of 30 percent if he crime was committed before 17 February 2010. Group D includes prisoners convicted of crimes that were eligible for 30-percent sentence reductions if committed before 17 February 2010 or after 1 July 2011.

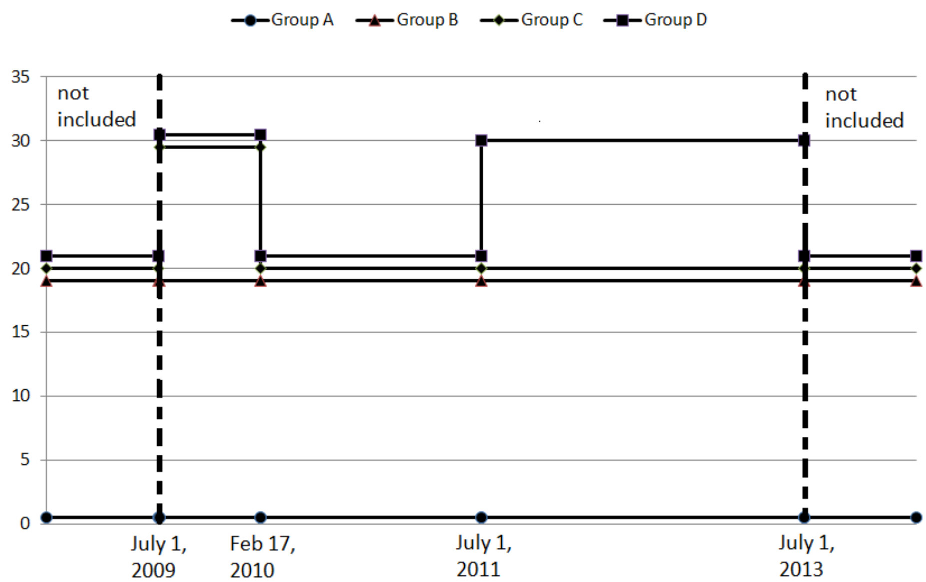
misconducts. As only major misconducts determine sentence reductions—major misconducts account for 94 percent of all misconducts—we will limit out attention to major misconducts and choose to drop the those above the 99^{th} percentile.[11] In Table 3.1 we report summary statistics, where we also group crimes into categories that will reflect the policy experiments we follow.

In Figure 3.1 we depict the policy-driven variation in available sentence reductions. Within our sample period, the sentence-reduction regime a prisoner falls into is determined by the crime committed and the date on which the crime occurred.[12] While evidence of judicial discretion

[11]The distribution of major misconducts by prisoner sentence is highly skewed. The median prisoner does not commit a misconduct during their sentence and the mean value is 2.35 while the prisoner committing the most misconducts during their tenure was cited 168 times. The one percent sample we drop includes all prisoners committing more than 27 misconducts during their sentence.

[12]We assume the most-severe crime a prisoner is convicted of determines sentence-reduction treatment at the prisoner level.

FIGURE 3.1. Sentence-Reduction Maximums, by Crime and Date Committed



is present within the data, we rely on the identifying variation that exists across time within a given category of crime. We group crimes into four categories following the administrative rules related to sentence reduction. The most-severe crimes are never eligible for sentence reductions.[13] Prisoners having committed Group B crimes experience 20-percent sentence reductions throughout the period of our analysis. It is the other two groups that experience policy shocks directly; one experiencing a one-time change in available reduction and the other experiencing the same change only to to be reversed 16 months later.[14]

A delay in conviction following crime commission is expected. This difference is larger for those with violent or sex-related crimes, for example, and shorter among those with drug-related crimes. This raises suspicion that variation in this difference may also move systematically with unobservables as well as treatment as prisoners committing severe crimes relatively recently may not yet appear in the data. In our analysis, we exclude all prisoners committing crimes after the

[13]The ineligibility of these prisoners was established in Oregon by Measure 11. This policy, enacted in 1994 and later expanded to include more crimes excludes specific severe crimes from sentence reduction eligibility although in some cases judges are given discretion to allow for sentence reduction eligibility at a 20-percent rate. A complete list of crimes that are not eligible for sentence reductions of any kind can be found in Table 3.2.

[14]For those convicted before 1 July 2009, judge discretion determined whether they transitioned to 30-percent reduction in 2009. Not observing judges' determinations, we are not able to exploit within-prisoner variation for identification. Ultimately, we discard all prisoner-day observations associated with crimes committed before 1 July 2009.

TABLE 3.2. Crimes, Grouped According to Sentence-Reduction Regimes

Group A Crimes: Sentence reductions only by judge discretion		
	No judge discretion to award sentence reductions	
Murder	Rape I	Assault I
Arson I	Rape II	Display Child Sex
Kidnapping	Sexual Abuse I	Sodomy I
Kidnapping II	Manslaughter I	Robbery
	Judge discretion permits 20-percent sentence reductions	
Assault II	Manslaughter II	Robbery II
Unlawful Sexual Penetration I	Unlawful Sexual Penetration II	
Sodomy II	Compelling Prostitution	
Group B Crimes: 20% sentence reductions available throughout sample period		
Assault III	Criminally Negligent Homicide	Sex Abuse II
Assault IV	Rape III	Sodomy III
Group C Crimes: 30% sentence reductions available if committed between 1 July 2009 and 17 Feb 2010; 20% thereafter.		
Abandon Child	Abuse Of Corpse I & II	Aggravated Animal Abuse I
Aggravated Vehicular Homicide	Animal Abuse C Felony	Assault Law Enforcement Animal
Assault Public Safety Officer	Attempted Weapon Use	Unlawful Burglary I
Buy/Sell A Minor	Child Neglect I	Coercion
Cause Person To Ingest Dangerous Substance	Criminal Mistreatment I	Custodial Sexual Misconduct I
Driving Under Influence Felony	Encouraging Child Sex Abuse I	Encouraging Child Sex
Abuse II	Encouraging Child Sex Abuse III	Escape I
Firearm - Pointing At Another	Firearm Used In Felony	Harassment Aggravated
Hit Run With Injury	Incest	Intimidation I
Involuntary Servitude I	Luring A Minor	Maintaining Dangerous Dog
Online Sex Corrupt Child I & II	Pay To View Child Pornography	Poss Of Hoax Destructive Device
Possess Child Porn Material I, II, & III	Possess Child Pornography	Possession Body Armor
Prostitution Promotion	Public Indecency	Racketeer Activity
Robbery III	Sexual Assault Of Animal	Contribute to Sexual Delinquency of a Minor
Sexual Misconduct	Stalking Felony	Strangulation Felony
Supply Contraband	Theft By Extortion	Theft I Aggravated
Unlawful Contact With A Child	Use Mace, Tear Gas, or Stun Gun	Weapon Possession - Inmate
Weapon Use Unlawful		
Group D Crimes: 30% sentence reductions available if committed between 1 July 2009 and 17 Feb 2010, or after 1 July 2013; 20% elsewhere.		
(All crimes not in groups A, B, or C.)		

Notes: Attempting to commit any of these crimes also qualifies them in the same category.

most-recent policy change of 1 July 2013 as well as those convicted more than two years after committing their crimes. By doing so, we ensure that the prisoners included in our sample across the treatment thresholds are as similar as possible.

Methods

Our first approach to identifying the causal effect of sentence-reduction generosity is to exploit policy-induced time-series variation in available reductions to identify whether there are changes in misconduct rates in Oregon prisons. For example, around the 17 February 2010 regime change, we will estimate RD models of the sort,

$$\begin{aligned} M_{it} = {} & \alpha + \beta 1(CrimeDate > 17Feb2010) + \theta CrimeDate_t \\ & + \psi CrimeDate_t 1(CrimeDate_t > 17Feb2010) + \epsilon_{it} \end{aligned} \tag{3.1}$$

where M_{it} is the number of major misconducts committed on day t by prisoners i, and β captures the treatment effect of 30-percent sentence reductions on misconducts. As usual, this model measures the local average treatment effect by considering the difference in the estimated conditional expectations of M_{it} on each side of the treatment threshold.

$$\lim_{r \uparrow c} \mathbb{E}[M_{it} \mid CrimeDate_i = 17Feb2010] - \lim_{r \downarrow c} \mathbb{E}[M_{it} \mid CrimeDate_{it} = 17Feb2010]. \tag{3.2}$$

In preferred specifications, we will also include a set of variables that flexibly control for the prisoner characteristics including number of total and violent convictions, age, race, sentence length, days served up to that point, ten categories of crime, and facility fixed effects for both the facility the prisoner was initially assigned to and the facility they were ultimately released from (or the facility they reside in at the end of our sample if they have yet to be released).[15] In estimating standard errors we allow for clustering at the crime-date level.

In Figure 3.2 we see the evidence of the regime changes, which will serve as the source of exogenous variation we exploit for identification in subsequent analysis. In Table 3.3 we confirm

[15]These crime categories are violent crimes, drug-related crimes, white collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, sex related crimes, and then a category for all others.

TABLE 3.3. Are Prisoners More Likely to Be Found on 30 Percent After 17 Feb 2010?

	All Prisoners (1)	Group A (2)	Group B (3)	Group C (4)	Group D (5)
Treatment (intended)	0.54067***	0.12212	0.00240	0.77731***	0.50665***
	(0.04815)	(0.23761)	(0.16331)	(0.06169)	(0.06704)
Crime Date	-0.00032	0.00062	-0.00079	0.00051	-0.00090
	(0.00060)	(0.00303)	(0.00105)	(0.00083)	(0.00089)
(Crime Date)^2	0.00000	-0.00000	0.00000	-0.00000	0.00000
	(0.00000)	(0.00001)	(0.00000)	(0.00000)	(0.00000)
Crime Date × Treatment	-0.00071	-0.00576	-0.00045	-0.00146	-0.00014
	(0.00103)	(0.00519)	(0.00310)	(0.00129)	(0.00141)
(Crime Date × Treatment)^2	-0.00001	-0.00002	-0.00001	-0.00000	-0.00001
	(0.00000)	(0.00002)	(0.00001)	(0.00001)	(0.00001)
Observations	2841	154	200	879	1608

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. t-statistics in parentheses. "Treatment" equal to one for those crimes committed before 17 February 2010, and therefore intended to move to 30-percent.

the existence of a first stage econometrically for prisoners in groups C and D around 17 February 2010 and, in Table 3.4, for Group D prisoners around 1 July 2011.

Standard RD-Validation Checks

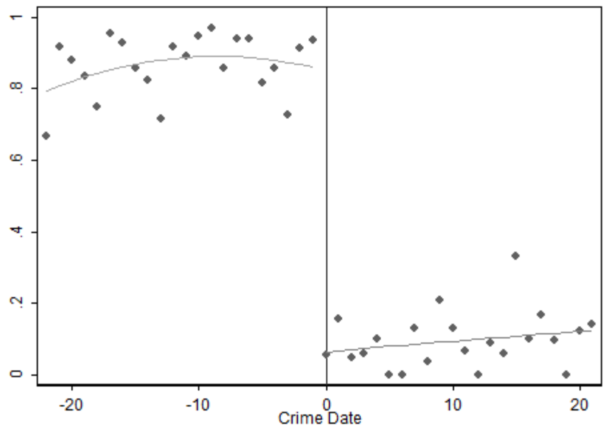
Before continuing to consider rates of misconduct around the treatment thresholds available for identification, we first pause to establish that observable characteristics and the distribution of the running variable are smooth around these thresholds. While it may be surprising to see in corrections data, violating these smoothness assumptions is usually taken as evidence that there is manipulation of the running variable. In Table 3.5 we consider whether observable characteristics are smooth through the threshold, raising no surprises and supporting the legitimacy of our methods. In Figure 3.3 we follow McCrary (2008) to further confirm that there is no discontinuity in the distribution across the treatment threshold. Thus, we proceed to anticipate that the estimated parameters retrieved from our regression-discontinuity design will facilitate making causal inference.

Results

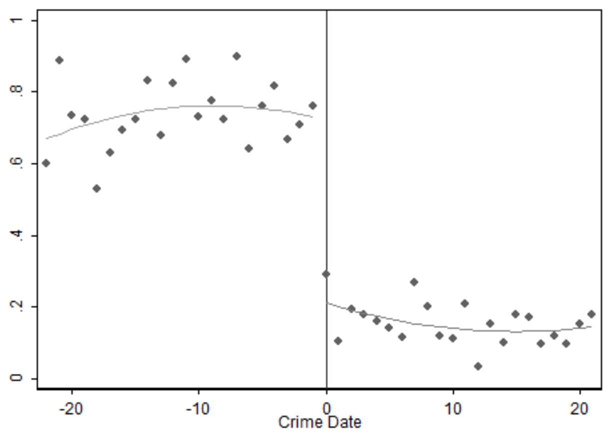
In Figure 3.4 we see a visual representation of the RD estimates, with crime dates gathered in ten-day bins. Only among Group C prisoners is there the appearance of a discontinuity in

FIGURE 3.2. Policy-Induced Variation in Available Sentence Reductions, by Crime Group

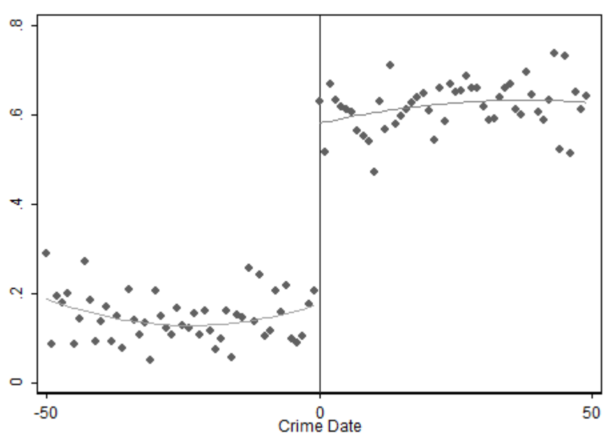
RD: Group C, 17 Feb 2010



RD: Group D, 17 Feb 2010



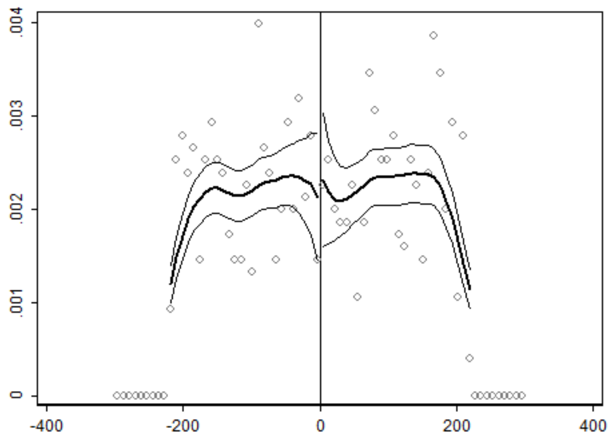
RD: Group D, 1 July 2011



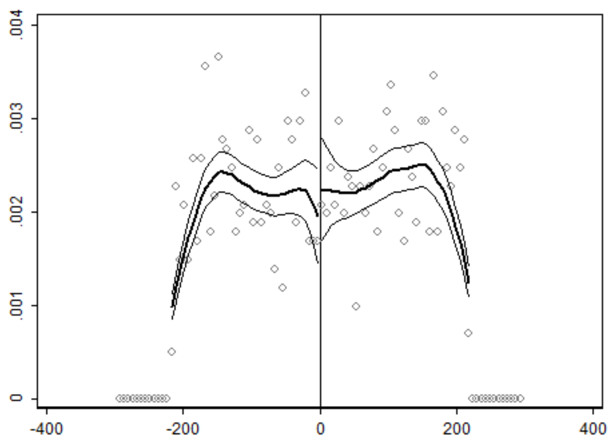
Notes: Each plot indicates the fraction of prisoners assigned to the indicated group eligible for 30% sentence reductions. Treatment is based on the date of the prisoner's crime and the type of crime committed (as this determines their group). The X-axis in each picture indicates 10 day crime date bins.

FIGURE 3.3. Is There Sorting Across the Threshold (McCrary, 2008)

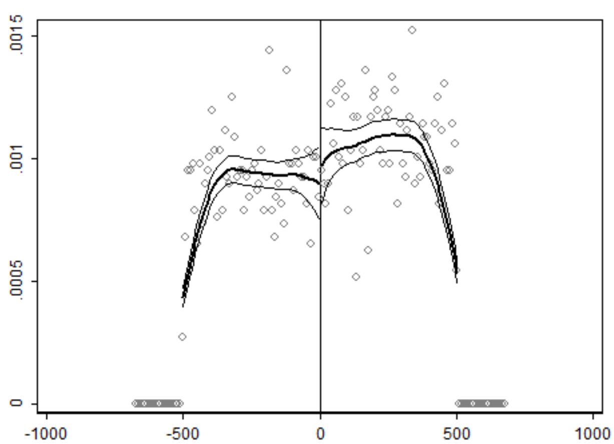
RD: Group C Prisoners, 17 Feb 2010



RD: Group D Prisoners, 17 Feb 2010



RD: Group D Prisoners, 1 July 2011



Notes: Each point indicates the number of prisoners eventually convicted of crimes committed on the indicated dates. Fitted values and 95% confidence intervals were generated using the DCdensity ado file developed by McCrary (2009).

TABLE 3.4. Are Prisoners More Likely to Be Found on 30 Percent After 1 July 2011?

	All Prisoners	Group A	Group B	Group C	Group D
	(1)	(2)	(3)	(4)	(5)
Treatment (intended)	0.29561***	0.14061	-0.10844*	0.21445***	0.40423***
	(0.03174)	(0.12451)	(0.05685)	(0.05283)	(0.04414)
Crime Date	0.00027*	0.00060	0.00025	-0.00006	0.00041*
	(0.00016)	(0.00078)	(0.00041)	(0.00025)	(0.00023)
(Crime Date)^2	0.00000*	0.00000	0.00000	-0.00000	0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Crime Date × Treatment	-0.00008	-0.00068	0.00138**	-0.00023	-0.00012
	(0.00029)	(0.00113)	(0.00065)	(0.00048)	(0.00040)
(Crime Date × Treatment)^2	-0.00000	-0.00000	-0.00000***	0.00000	-0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	7054	451	390	2146	4067

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. t-statistics in parentheses. "Treatment" equal to one for those crimes committed after 1 July 2011, and therefore intended to move to 30-percent.

misconduct rates associated with treatment—lower rates on the "treatment" side of the threshold, where 30-percent sentence reductions are available.

In Table 3.6 we present the simplest of our specifications, separately allowing for quadratic trends on either side of the treatment threshold and identifying any discontinuity in misconduct rates among Group C prisoners with the 17 February 2010 policy change. Though somewhat imprecisely measured, around this policy experiment, there is no apparent change in misconduct rates across treatment and control regimes. In Column (2) we add prisoner controls and in Column (3) we further add facility fixed effects. In no specification can one conclude that sentence-reduction generosity influences misconduct rates in a significant way. We repeat this analysis for Group D prisoners around the two regime changes such prisoners experienced on 17 February 2010 and 1 July 2011, with results reported in tables 3.7 and 3.8. Again, there is no evidence of systematic improvement in behavior coincident with more-generous sentence reductions.

It is possible that the significant skewness of the misconduct distribution allows for outliers to mask the true effect of the policy changes. As such, we next consider whether the generosity of sentence reductions impacts the extensive margin of prisoner misconduct. Thus in Tables 3.9, 3.10, and 3.11 we replace total misconducts with an indicator variable, equal to one if the prisoner

TABLE 3.5. Covariate Smoothness Across Treatment Thresholds

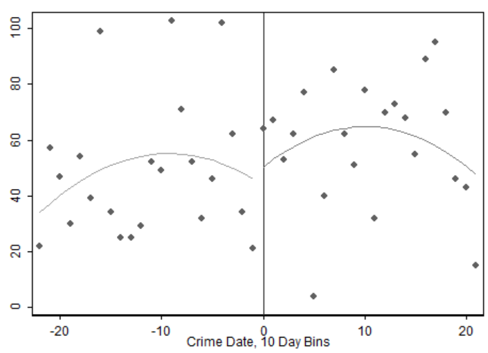
	RD: 17 February 2010			RD: 1 July 2011		
	Group B	Group C	Group D	Group B	Group C	Group D
Days from Crime to Conviction	25.04	42.21*	7.88	-38.66	23.96	-10.39
	(51.79)	(24.92)	(17.50)	(35.42)	(15.22)	(10.97)
Total Crime Convictions	-0.04	0.20	0.37**	-0.09	-0.04	-0.08
	(0.31)	(0.32)	(0.17)	(0.31)	(0.19)	(0.10)
Violent Crime Convictions	-0.03	0.09	0.02	-0.21	0.08*	-0.05
	(0.23)	(0.08)	(0.07)	(0.18)	(0.04)	(0.04)
Sentence Length	-3.84	-28.01	95.67	-75.75	-41.38	54.88
	(141.86)	(151.88)	(84.73)	(51.08)	(36.48)	(37.44)
Age	-0.62	-0.87	1.75	0.33	-2.34***	-1.25***
	(2.93)	(1.65)	(1.08)	(1.06)	(0.49)	(0.33)
White	0.14	-0.02	0.04	0.01	0.05**	0.02
	(0.13)	(0.06)	(0.05)	(0.04)	(0.02)	(0.01)
Black	-0.05	0.01	-0.00	0.02	-0.01	-0.00
	(0.08)	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
Hispanic	-0.14	0.00	-0.02	-0.01	-0.05***	-0.01
	(0.11)	(0.04)	(0.04)	(0.03)	(0.01)	(0.01)
ACRS Score	0.02	0.02	0.05***	0.01	0.01	0.02***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Recidivists	0.10	0.03	0.08	0.06	-0.04*	-0.01
	(0.11)	(0.07)	(0.05)	(0.04)	(0.02)	(0.02)
Parole Violators	-0.13	0.02	-0.03	-0.01	-0.04	-0.03**
	(0.10)	(0.05)	(0.04)	(0.04)	(0.02)	(0.01)
Observations	200	879	1,608	390	2,146	4,067

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Each cell reports the estimated coefficient of a separate regression of treatment (to 30-percent sentence reduction) on the covariate and a crime-date trend as the only independent variables. Robust standard errors reported in parentheses.

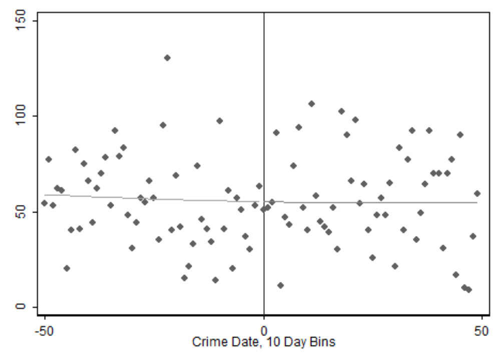
FIGURE 3.4. RD Plots by Group and Policy Change

Panel A: Major Misconducts, Group C Prisoners

RD: 17 Feb 2010

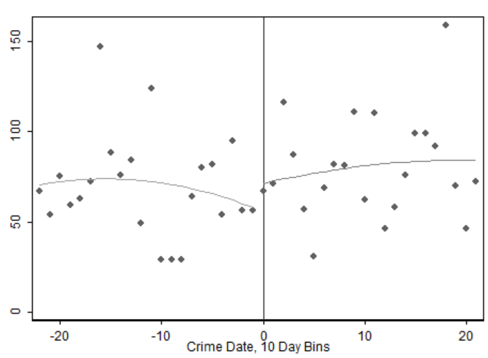


RD: 1 July 2011 (falsification)

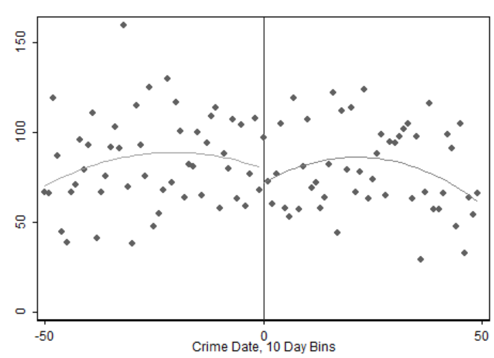


Panel B: Major Misconducts, Group D Prisoners

RD: 17 Feb 2010



RD: 1 July 2011



Notes: Each plot represents the number of major misconducts committed by all prisoners over the course of their sentences falling into the indicated 10 day bin based on their group and the date on which their crime was committed. Fitted lines are based on a simple regression that includes only a treatment dummy and flexible time trends before and after treatment.

TABLE 3.6. Major Misconducts, Group C Prisoners, 17 Feb 2010

	(1)	(2)	(3)
30-Percent	-0.87962	-0.60734	-0.28334
	(0.81431)	(0.75495)	(0.71799)
Crime Date	0.00338	0.00219	0.00661
	(0.01263)	(0.01160)	(0.01026)
(Crime Date)^2	-0.00002	-0.00002	-0.00004
	(0.00005)	(0.00005)	(0.00004)
Crime Date × Treatment	-0.01825	-0.01351	-0.01484
	(0.01674)	(0.01514)	(0.01396)
(Crime Date × Treatment)^2	-0.00005	-0.00004	-0.00001
	(0.00007)	(0.00007)	(0.00006)
Conviction Date - Crime Date		-0.00130*	-0.00119*
		(0.00072)	(0.00066)
Days Served		0.00897***	0.00551**
		(0.00197)	(0.00250)
(Days Served)^2		-0.00000**	-0.00000
		(0.00000)	(0.00000)
Observations	879	879	879
Mean Misconducts	2.95	2.95	2.95
Prisoner Controls	No	Yes	Yes
Facility FE	No	No	Yes

Notes: * p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. The sample includes all Group C prisoners who committed crimes between 1 July 2009 and 21 September 2010 (+/- 216 of the policy change), other than those in the top percentile of total major misconducts commit throughout prisoner sentences (i.e., more than 33). Controls include number of total and violent convictions, age, race, sentence length, and shifters for violent crimes, drug-related crimes, white-collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, and sex-related crimes.

TABLE 3.7. Major Misconducts, Group D Prisoners, 17 Feb 2010

	(1)	(2)	(3)
30-Percent	-0.36875	-0.08713	-0.32972
	(0.56290)	(0.51874)	(0.48141)
Crime Date	-0.00415	-0.00339	-0.00952
	(0.00874)	(0.00848)	(0.00817)
(Crime Date)^2	0.00002	0.00002	0.00004
	(0.00004)	(0.00004)	(0.00003)
Crime Date × Treatment	0.00787	0.00743	0.01501
	(0.01288)	(0.01181)	(0.01118)
(Crime Date × Treatment)^2	0.00001	0.00001	-0.00001
	(0.00006)	(0.00005)	(0.00005)
Conviction Date - Crime Date		-0.00121***	-0.00067
		(0.00042)	(0.00041)
Days Served		0.00709***	0.00454***
		(0.00157)	(0.00139)
(Days Served)^2		-0.00000*	-0.00000
		(0.00000)	(0.00000)
Observations	1608	1608	1608
Mean Misconducts	2.11	2.11	2.11
Prisoner Controls	No	Yes	Yes
Facility FE	No	No	Yes

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. The sample includes all Group D prisoners who committed crimes between 1 July 2009 and 21 September 2010 (+/- 216 of the policy change), other than those in the top percentile of total major misconducts commit throughout prisoner sentences (i.e., more than 33). Controls include number of total and violent convictions, age, race, sentence length, and shifters for violent crimes, drug-related crimes, white-collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, and sex-related crimes.

TABLE 3.8. Major Misconducts, Group D Prisoners, 1 July 2011

	(1)	(2)	(3)
30-Percent	-0.41192	-0.23531	-0.22477
	(0.34147)	(0.30233)	(0.29261)
Crime Date	-0.00085	-0.00017	0.00014
	(0.00248)	(0.00224)	(0.00215)
(Crime Date)^2	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)
(Crime Date $\times$ Treatment)	0.00261	0.00093	-0.00025
	(0.00318)	(0.00277)	(0.00267)
(Crime Date $\times$ Treatment)^2	-0.00000	-0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)
Conviction Date - Crime Date		-0.00037	-0.00049*
		(0.00028)	(0.00026)
Days Served		0.00650***	0.00519***
		(0.00111)	(0.00112)
(Days Served)^2		-0.00000**	-0.00000
		(0.00000)	(0.00000)
Observations	4067	4067	4067
Mean Misconducts	1.82	1.82	1.82
Prisoner Controls	No	Yes	Yes
Facility FE	No	No	Yes

Notes: * p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. The sample includes all Group D prisoners who committed crimes between 17 February 2010 and 10 November 2012 (+/- 499 of the policy change), other than those in the top percentile of total major misconducts commit throughout prisoner sentences (i.e., more than 33). Controls include number of total and violent convictions, age, race, sentence length, and shifters for violent crimes, drug-related crimes, white-collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, and sex-related crimes.

TABLE 3.9. Major Misconducts, Group C Prisoners: 17 Feb 2010 Extensive Margin

	(1)	(2)	(3)
30-Percent	-0.11201	-0.06344	-0.04342
	(0.09705)	(0.09016)	(0.08796)
Crime Date	-0.00049	-0.00105	-0.00063
	(0.00131)	(0.00129)	(0.00122)
$(\text{Crime Date})^2$	-0.00000	0.00000	0.00000
	(0.00001)	(0.00001)	(0.00001)
Crime Date $\times$ Treatment	-0.00026	0.00110	0.00089
	(0.00201)	(0.00194)	(0.00184)
$(\text{Crime Date} \times \text{Treatment})^2$	-0.00000	-0.00000	0.00000
	(0.00001)	(0.00001)	(0.00001)
Conviction Date - Crime Date		-0.00012	-0.00010
		(0.00009)	(0.00009)
Days Served		0.00136***	0.00073***
		(0.00017)	(0.00024)
$(\text{Days Served})^2$		-0.00000***	-0.00000**
		(0.00000)	(0.00000)
Observations	879	879	879
Mean Misconduct (0-1)	0.52	0.52	0.52
Prisoner Controls	No	Yes	Yes
Facility FE	No	No	Yes

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering at the crime-date level and are reported in parentheses. The sample includes all Group D prisoners who committed crimes between 1 July 2009 and 21 September 2010 (+/- 217 of the policy change), other than those in the top percentile of total major misconducts commit throughout prisoner sentences (i.e., more than 33). Controls include number of total and violent convictions, age, race, sentence length, and shifters for violent crimes, drug-related crimes, white-collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, and sex-related crimes.

ever committed a misconduct and zero otherwise. As in our previous models, we find no evidence that prisoner behavior is affected by the 50% increase in available sentence reductions.

Robustness and Heterogeneity Analysis

In tables 3.12, 3.13, 3.14, and 3.15 we further explore the potential for available sentence reductions to contribute to rates of prisoner misconduct by stratifying across prisoner age, a prior of each prisoner's likelihood of recidivism, education, and race, for each of the three regime changes.[16] Although some point estimates are large in magnitude, representing sizable effect sizes, in no case do we find significant changes in prisoner misconduct around treatment.

[16] On entry, all Oregon prisoners are assigned an Automated Criminal Risk Score (ACRS) to identify offenders most likely to recidivate. ACRS ranges from 0 to 1 with lower scores indicating a reduced probability to recidivate.

TABLE 3.10. Major Misconducts, Group D Prisoners: 17 Feb 2010 Extensive Margin

	(1)	(2)	(3)
30-Percent	-0.03414	0.02709	0.01546
	(0.07208)	(0.07033)	(0.06857)
Crime Date	-0.00072	-0.00000	-0.00051
	(0.00116)	(0.00113)	(0.00111)
$(\text{Crime Date})^2$	0.00000	0.00000	0.00000
	(0.00001)	(0.00000)	(0.00000)
Crime Date $\times$ Treatment	0.00024	-0.00019	0.00057
	(0.00162)	(0.00153)	(0.00147)
$(\text{Crime Date} \times \text{Treatment})^2$	-0.00001	-0.00000	-0.00000
	(0.00001)	(0.00001)	(0.00001)
Conviction Date - Crime Date		-0.00020***	-0.00015*
		(0.00007)	(0.00007)
Days Served		0.00129***	0.00117***
		(0.00016)	(0.00020)
$(\text{Days Served})^2$		-0.00000***	-0.00000***
		(0.00000)	(0.00000)
Observations	1608	1608	1608
Mean Misconduct (0-1)	0.48	0.48	0.48
Prisoner Controls	No	Yes	Yes
Facility FE	No	No	Yes

Notes: * p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. The sample includes all Group D prisoners who committed crimes between 1 July 2009 and 21 September 2010 (+/- 217 of the policy change), other than those in the top percentile of total major misconducts commit throughout prisoner sentences (i.e., more than 33). Controls include number of total and violent convictions, age, race, sentence length, and shifters for violent crimes, drug-related crimes, white-collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, and sex-related crimes.

TABLE 3.11. Major Misconducts, Group D Prisoners: 1 July 2011 Extensive Margin

	(1)	(2)	(3)
30-Percent	-0.05826	-0.03004	-0.02565
	(0.04590)	(0.04318)	(0.04071)
Crime Date	-0.00004	0.00001	0.00001
	(0.00032)	(0.00030)	(0.00029)
(Crime Date)^2	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)
Crime Date × Treatment	0.00011	-0.00016	-0.00025
	(0.00043)	(0.00040)	(0.00039)
(Crime Date × Treatment)^2	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)
Conviction Date - Crime Date		-0.00008*	-0.00009*
		(0.00005)	(0.00004)
Days Served		0.00147***	0.00129***
		(0.00012)	(0.00013)
(Days Served)^2		-0.00000***	-0.00000***
		(0.00000)	(0.00000)
Observations 4067	4067	4067	
Mean Misconduct (0-1)	0.51	0.51	0.51
Prisoner Controls	No	Yes	Yes
Facility FE	No	No	Yes

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. The sample includes all Group D prisoners who committed crimes between 17 February 2010 and 10 November 2012 (+/- 499 of the policy change), other than those in the top percentile of total major misconducts commit throughout prisoner sentences (i.e., more than 33). Controls include number of total and violent convictions, age, race, sentence length, and shifters for violent crimes, drug-related crimes, white-collar crimes, theft, parole violation, vandalism, gun-related crimes, child-sex crimes, and sex-related crimes.

TABLE 3.12. Heterogeneity: Prisoner Age

	RD: 17 February 2010		RD: 1 July 2011
	Group C (1)	Group D (2)	Group D (3)
Prisoners 26 and younger			
30-Percent	-0.59698	0.02694	-0.13745
	(2.04289)	(1.40012)	(0.87306)
Observations	229	314	931
Mean Misconducts	5.34	3.49	3.92
Prisoners in [27,33]			
30-Percent	-1.57476	0.34427	-1.11502**
	(1.80170)	(0.86708)	(0.48077)
Observations	217	429	1102
Mean Misconducts	3.37	2.29	2.40
Prisoners in [34,43]			
30-Percent	-2.13337*	-1.47839	-0.13968
	(1.11689)	(0.90995)	(0.45452)
Observations	207	427	1061
Mean Misconducts	1.98	2.07	1.81
Prisoners 44 and older			
30-Percent	0.53486	0.07884	0.34243
	(0.74604)	(0.48653)	(0.49585)
Observations	208	404	883
Mean Misconducts	1.07	1.02	1.13

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering at the crime-date level and are reported in parenthesis.

TABLE 3.13. Heterogeneity: ACRS Scores

	RD: 17 February 2010		RD: 1 July 2011
	Group C (1)	Group D (2)	Group D (3)
1^{st}-quartile ACRS Scores			
30-Percent	0.46387	-0.95213	0.45901
	(1.08196)	(1.06579)	(0.59565)
Observations	224	358	812
Mean Misconducts	2.50	1.80	1.68
2^{nd}-quartile ACRS Scores			
30-Percent	-0.97204	0.30537	-1.05491
	(1.66527)	(0.90066)	(0.76855)
Observations	280	379	860
Mean Misconducts	3.12	2.53	2.67
3^{rd}-quartile ACRS Scores			
30-Percent	-1.32820	-1.24001	0.35921
	(1.87996)	(1.05588)	(0.53189)
Observations	203	426	1097
Mean Misconducts	3.06	2.16	2.23
4^{th}-quartile ACRS Scores			
30-Percent	0.01396	-0.13384	-0.78041
	(1.67713)	(0.74918)	(0.51630)
Observations	152	445	1298
Mean Misconducts	3.40	2.02	2.27

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering at the crime-date level and are reported in parenthesis.

TABLE 3.14. Heterogeneity: Education

	RD: 17 February 2010		RD: 1 July 2011
	Group C (1)	Group D (2)	Group D (3)
GED or Less Education			
30-Perent	-0.11330	-0.18996	-0.16938
	(0.89762)	(0.52596)	(0.33367)
Observations	668	1254	3029
Mean Misconducts	3.12	2.20	2.31
HSD or More Education			
(mean) regime30_first	-1.12450	-0.48418	0.04689
	(1.67427)	(0.84709)	(0.65243)
Observations	211	354	1038
Mean Misconducts	2.36	1.86	1.94

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parenthesis.

In tables 3.16, 3.17, and 3.18 we consider (for each policy experiment) the potential for non-linearities in treatment across sentence served. Specifically, we allow for the effect of sentence reduction generosity on major misconducts to vary across the first 30 days served, second thirty days served, and so on. Again, there is no such response evident in major misconducts, or in drug misconducts, violent misconducts, or when misconducts are separated by whether they involved single or multiple prisoners.

Six-Month-Review Cycles

Background

The administrative-review cycles for prisoner incentives provide several predictions assuming Beckerian models of deterrence (Becker, 1974). Early in the review cycle, prisoners should commit more misconducts because the expected returns to behaving well on a particular day are lower due to the number of future days on which a prisoner also has to behave well in order to earn sentence reductions. Likewise, later in the review cycles inmates should commit fewer misconducts due to the decreased interval over which they must avoid misconducts.

TABLE 3.15. Heterogeneity: Race

	RD: 17 February 2010		RD: 1 July 2011
	Group C (1)	Group D (2)	Group D (3)
White Prisoners			
30-Percent	-0.45378	-0.38235	-0.41289
	(0.63908)	(0.53669)	(0.32633)
Observations	651	1176	3024
Mean Misconducts	2.47	2.17	2.24
Black Prisoners			
30-Percent	-3.10832	1.77376	1.96361
	(2.65282)	(1.68438)	(1.36698)
Observations	100	136	369
Mean Misconducts	2.48	2.05	2.18
Hispanic Prisoners			
30-Percent	4.48425	0.31558	0.03822
	(5.78309)	(1.39818)	(0.72550)
Observations	102	241	541
Mean Misconducts	4.21	2.28	2.23

Notes: * p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parenthesis.

TABLE 3.16. Misconducts, Group C: 17 Feb 2010 Extensive Margin Across Days Served

	0 - 30	31 - 60	61 - 90	91 - 180	0 - 180
	(1)	(2)	(3)	(4)	(5)
Major Misconducts	-0.03443	-0.06110	0.00657	0.03520	-0.06479
	(0.05249)	(0.06990)	(0.06761)	(0.08280)	(0.09640)
Mean	0.04	0.07	0.10	0.20	0.32
Drug Misconducts	-0.00056	-0.00123	0.00259	-0.01165	-0.00963
	(0.00466)	(0.00580)	(0.01129)	(0.03136)	(0.03082)
Violent Misconducts	-0.01509	-0.01217	-0.00939	0.05869	0.00867
	(0.02406)	(0.03657)	(0.03506)	(0.05066)	(0.07094)
Single-Person Misconducts	-0.01421	-0.01502	0.03411	0.05132	-0.00788
	(0.02080)	(0.03546)	(0.05177)	(0.06373)	(0.8700)
Multi-Person Misconducts	-0.03961	-0.01184	0.01244	-0.01728	-0.05679
	(0.04894)	(0.05504)	(0.04869)	(0.07390)	(0.08425)

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. Each cell reports the estimated coefficient of a separate regression that captures the propensity to observe non-zero misconduct counts for given categories of misconduct and within samples restricted to each prisoners' first 30 days, second 30 days, etc..

TABLE 3.17. Misconducts, Group D: 17 Feb 2010 Extensive Margin Across Days Served

	0 - 30	31 - 60	61 - 90	91 - 180	0 - 180
	(1)	(2)	(3)	(4)	(5)
Major Misconducts	-0.05358	-0.05260	0.01447	-0.05742	-0.10396*
	(0.03609)	(0.03678)	(0.04326)	(0.06106)	(0.06169)
Mean	0.05	0.06	0.09	0.21	0.31
Drug Misconducts	0.00080	0.00176	-0.00151	0.00148	0.00657
	(0.00125)	(0.00333)	(0.01004)	(0.01944)	(0.02303)
Violent Misconducts	0.01541	-0.00875	0.01419	-0.01116	0.01119
	(0.02075)	(0.02708)	(0.01398)	(0.03257)	(0.04589)
Single Person Misconducts	-0.03283*	-0.02586	-0.03798	-0.02733	-.10373**
	(0.01732)	(0.02298)	(0.02486)	(0.04147)	(0.04895)
Multi Person Misconducts	-0.01974	-0.02489	0.01753	-0.02668	-0.01998
	(0.02826)	(0.03038)	(0.02796)	(0.05104)	(0.06091)

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering at the crime-date level and are reported in parentheses. Each cell reports the estimated coefficient of a separate regression that captures the propensity to observe non-zero misconduct counts for given categories of misconduct and within samples restricted to each prisoners' first 30 days, second 30 days, etc..

TABLE 3.18. Misconducts, Group D: 1 July 2011 Extensive Margin Across Days Served

	0 - 30	31 - 60	61 - 90	91 - 180	0 - 180
	(1)	(2)	(3)	(4)	(5)
Major Misconducts	0.01042	-0.02218	-0.00844	-0.00514	-0.01257
	(0.01932)	(0.02437)	(0.02479)	(0.03728)	(0.04224)
Mean	0.05	0.07	0.07	0.19	0.30
Drug Misconducts	-0.00136	-0.01186	0.00107	-0.01322	-0.02110
	(0.00274)	(0.00758)	(0.00697)	(0.01604)	(0.01884)
Violent Misconducts	0.00615	-0.00188	-0.01758	0.03651*	0.00019
	(0.01333)	(0.01186)	(0.01537)	(0.02006)	(0.02626)
Single Person Misconducts	-0.01012	-0.02398	0.01368	-0.05297**	-0.07845***
	(0.01097)	(0.01530)	(0.01604)	(0.02530)	(0.03020)
Multi Person Misconducts	0.01516	-0.02525	-0.01912	0.01912	-0.00011
	(0.01795)	(0.01699)	(0.02025)	(0.03180)	(0.03648)

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering at the crime-date level and are reported in parentheses. Each cell reports the estimated coefficient of a separate regression that captures the propensity to observe non-zero misconduct counts for given categories of misconduct and within samples restricted to each prisoners' first 30 days, second 30 days, etc..

This implies that if we were able to control for other potentially confounding factors, the number of misconducts should be positively related to the number of days from the next review. Furthermore, there should also be a jump in misconduct rates at the start of a new review cycle due to the discontinuity in deterrence around the assessment period. As a preliminary analysis, then, we first estimate whether the number of days until a subsequent review is positively related to the number of misconducts.

The discontinuous incentive structure around the end of review cycles naturally lends itself to a regression discontinuity model as one approach to identifying whether the review cycles alter prisoner behavior—the estimated discontinuity reflects the degree to which misconduct rates tend to vary between the first and last days of the average review period. First introduced by (Thistlethwaite and Campbell, 1960), regression discontinuity (RD) offers a useful approach to identify the causal effect of treatments when treatment status is determined by a discontinuity in another variable. In our case, the variable that determines treatment is the days from review. In order for an RD to produce unbiased estimates, any variation in either observable or unobservable characteristics should remain smooth through the threshold where the discontinuity occurs (Hahn, Todd, and Van der Klaauw, 2001).

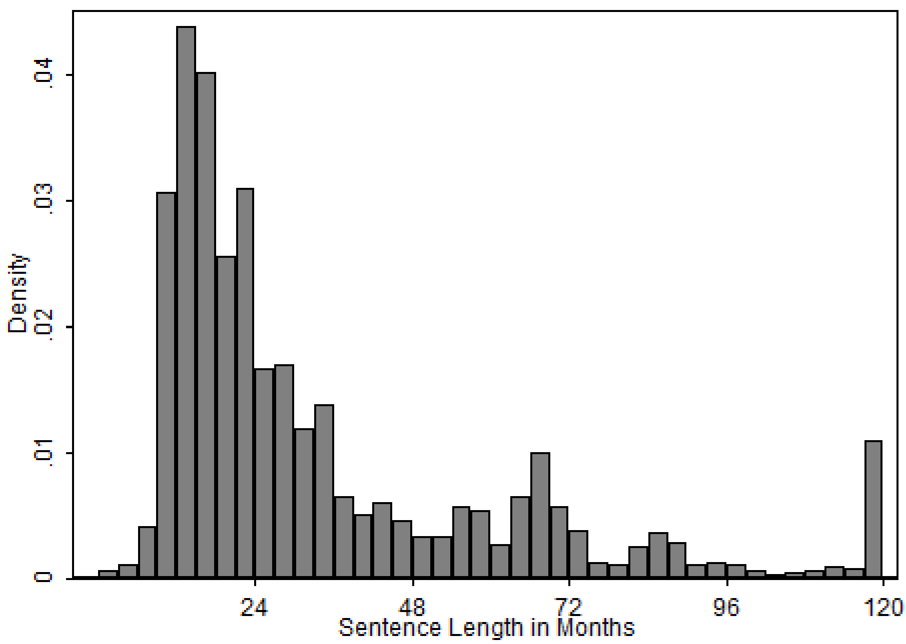
The main threat to these assumptions in our case will be the timing of when inmates leave prison. As shown in Figure 3.5, there is substantial variation in assigned sentence length, and possibly some heaping in particular sentence lengths, which might challenge identification if any such discontinuities in the density of the running variable reveal an underlying non-random selection out of the sample around a review period (McCrary, 2008). However, when we examine a histogram the number of days since inmates entered prison, as in Figure 3.6, there is no evidence of discontinuous exit patterns.[17] To ensure that exit issues do not arise, we restrict our attention to prisoners with adjacent six-months reviews. While this causes abrupt decreases in the "days served" histogram, it creates a perfectly balanced, uniform density when we rescale the number of days individuals have served around the thresholds. With no exit from the sample, by construction, the density is uniform across the threshold and the relevant density tests (McCrary (2008) and Frandsen (2013)) therefore raise no concerns.

Methodology and Results

In this section we consider whether there is any systematic discontinuity in prisoner misconducts coincident with what we have argued is a discontinuity in each prisoner's incentives on the day of assessment. Again, assuming they have behaved well up until that point, prisoners who are one-day shy of their next evaluation only have to behave well for one additional day to earn their entire available sentence reductions for that period. However, on the day following an assessment, in order to earn the reward prisoners must forecast behaving well for that and all remaining days until their next assessment. Due to the uncertainty surrounding their ability to behave well for the entire six-month span, the expected returns to behaving well should be much higher on the day just prior to the assessment than on the day immediately following an assessment–it is this discontinuity that we exploit for identification.

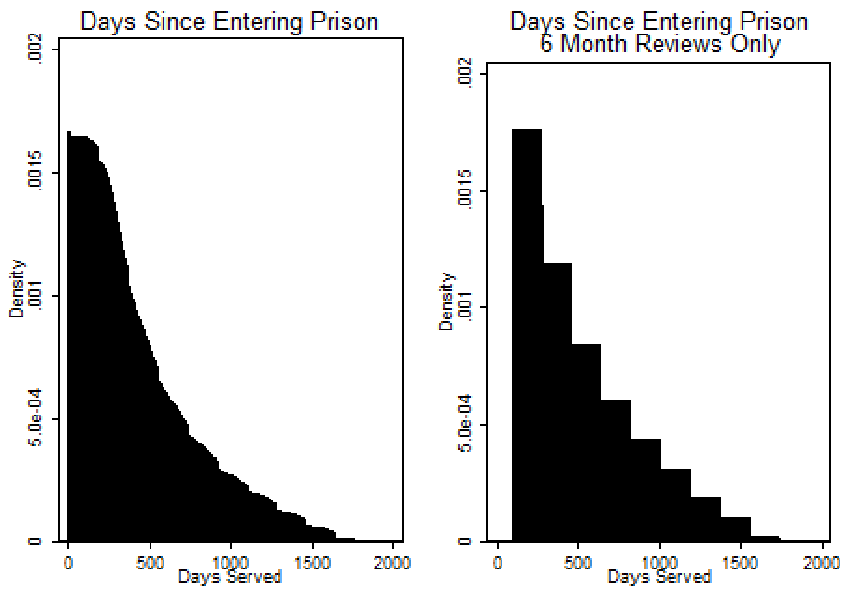
[17]This likely happens become of quasi-random variation in the amount of "time-served" inmates have upon entered prison depending on their trial length and whether they were originally jail, and variation due to the earned sentence reductions themselves. In addition, many prisoners in our sample have not-yet completed their sentence. In these cases the maximum value of days served is simply the difference between the last day of our sample and the day the prisoner entered prison.

FIGURE 3.5. Sentence Lengths



Notes: Results based on the population of male prisoners convicted of crimes in Oregon committed after June 30, 2009 and before July 1, 2013. We include all prisoner-days from entry until the earlier of the prisoner's release and June 30, 2014. All sentence lengths longer than 120 months were top-coded to 120 months. These sentences represent the maximum number of days a prisoner could serve if they are not convicted of additional crimes while incarcerated.

FIGURE 3.6. Days Since Entering Prison



Notes: Results based on the population of male prisoners convicted of crimes in Oregon committed after June 30, 2009 and before July 1, 2013. We include all prisoner-days from entry until the earlier of the prisoner's release and June 30, 2014. In Panel A, we plot days served for each prisoner. In Panel B, the sample is limited to prisoners serving consecutive six-month review periods.

In so doing, we construct "synthetic" assessment periods that begin 89 days prior to the day of assessment and last until 89 days after assessment.[18] In the two related analyses that follow, we separately consider the potential discontinuity in misconduct rates coincident with assessment.

Identifying changes in misconduct rates around assessment

Let M_{dap} be counts of major misconducts on day d in synthetic-assessment period a of prisoner p. Days are organized for each prisoner in relation to his day of evaluation, so $d = -1$ is the day before prisoner p's evaluation, $d = 0$ is the day of prisoner p's evaluation, and so on; d ranges from -89 to 89 Thus, we define $DFA_{dap} \in [-89, 89]$ as the days from assessment. The econometric model is therefore of the form,

$$\begin{aligned} M_{dap} &= \alpha + \gamma_1 1(DFA_{dap} \geq 0) + \gamma_2 DFA_{dap} \\ &\quad + \gamma_3 DFA_{dap} \times 1(DFA_{dap} \geq 0) + \mu_{dap}, \end{aligned} \tag{3.3}$$

where μ_{dap} is a random error term. In (3.3), the local average treatment effect, $\hat{\gamma}_1$, is identified by considering the difference in the estimated conditional expectations of M_{dap} on each side of the treatment threshold,

$$\lim_{r \uparrow 0} \mathbb{E}[M_{dap} \mid DFA_{dap} = r] - \lim_{r \downarrow 0} \mathbb{E}[M_{dap} \mid DFA_{dap} = r]. \tag{3.4}$$

In the context of the traditional regression-discontinuity design, observations for which $DFR_{dap} \geq 0$ are therefore "treated," with observations for which $DFR_{dap} < 0$ serving as the control, together allowing us to retrieve an estimate of the change in average misconduct rates across the discontinuity.

In Table 3.19 we first reproduce $\hat{\gamma}_1$ from (3.3) among all prisoners eligible for sentence reductions. Then, in subsequent columns, we reproduce $\hat{\gamma}_1$ after adding controls (i.e., indicators of number of convictions, number of violent convictions, age decile, race, sentence-length decile crime type, day of week, month, and year) in Column (2), facility by month fixed effects, as prisoner

[18] Six month review cycles last between 180 and 184 days including the day of the review. In order to ensure that the sample of prisoners on each side of the review is identical, we impose a maximum bandwidth of 89 days in either direction.

TABLE 3.19. Prisoner Behavior Around 6 Month Review Cycles: Groups B, C, and D

	(1)	(2)	(3)	(4)
New Review Period	0.00014	0.00008	0.00008	0.00008
	(0.00025)	(0.00025)	(0.00026)	(0.00026)
Days Until Review	-0.00044	0.00002	-0.00003	-0.00004
	(0.00034)	(0.00035)	(0.00036)	(0.00036)
Days After Review	-0.00032	-0.00047	-0.00041	-0.00040
	(0.00048)	(0.00048)	(0.00048)	(0.00048)
Regime (=1 if 30%)		0.00014	0.00019	0.00019
		(0.00013)	(0.00015)	(0.00015)
Days Served		-0.00001***	-0.00000***	-0.00000***
		(0.00000)	(0.00000)	(0.00000)
Days Served Squared		0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)
Black		0.00034	0.00044	0.00044
		(0.00025)	(0.00028)	(0.00028)
Hispanic		0.00020	-0.00027	-0.00028
		(0.00022)	(0.00027)	(0.00027)
Other Race		0.00116***	0.00107***	0.00107***
		(0.00041)	(0.00040)	(0.00040)
Observations	2098180	2098180	2098180	2098180
Mean Misconducts	0.00402	0.00402	0.00402	0.00402
Prisoner Controls	No	Yes	Yes	Yes
Facility × Month FE	No	No	Yes	Yes
Facility × Day-of-Week FE	No	No	No	Yes

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering at the facility-month level and are reported in parentheses. Only prisoner-review cycles in which a prisoner experienced at least 89 days both before and after a review are used to estimate these results. Shortened review cycles occur due to prisoner release.

behavior could vary systematically across facilities (e.g., through guard behavior) in Column (3), and facility by day-of-week fixed effects in Column (4). Largely invariant to the choice of specification, estimates in columns (1) through (4) suggest that daily misconduct rates do not change in the period following the review.

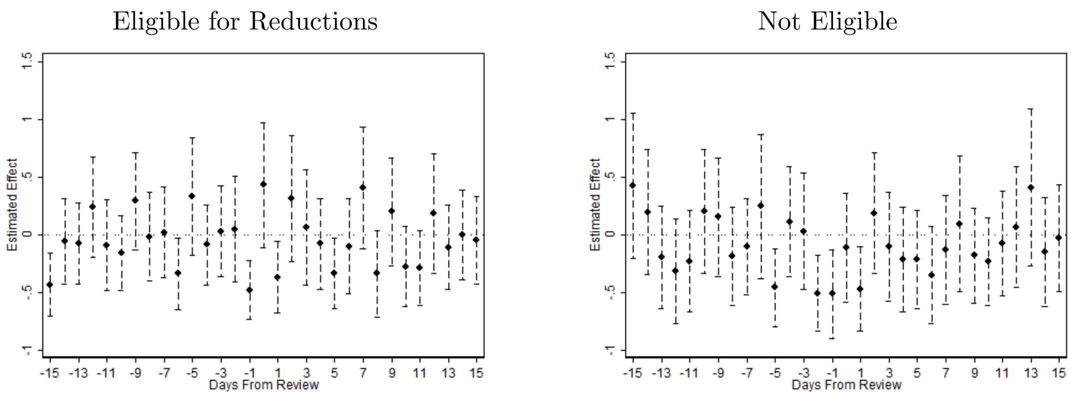
In Table 3.20 we estimate models identical to column (4) of Table 3.19, separately for prisoners in each crime group. While all groups of inmates have incentives to behave well around review cycles—even prisoners ineligible for sentence reductions face potential reductions in privileges like visitation and phone use in the six-month reviews—the incentives are much stronger for the prisoners who are eligible for sentencing reductions. As in the previous section, we find no evidence that any group of prisoners responds to the discontinuous change to incentives to behave well coincident with the review.

TABLE 3.20. Prisoner Behavior Around 6 Month Review Cycles - By Group

	Group A (1)	Group B (2)	Group C (3)	Group D (4)
New Review Period	-0.00040	0.00022	0.00031	-0.00010
	(0.00029)	(0.00092)	(0.00047)	(0.00036)
Days Until Review	0.00034	-0.00017	0.00015	-0.00019
	(0.00040)	(0.00123)	(0.00063)	(0.00050)
Days After Review	0.00072	0.00003	-0.00064	-0.00019
	(0.00058)	(0.00187)	(0.00085)	(0.00067)
Regime (=1 if 30%)			-0.00012	0.00016
			(0.00035)	(0.00019)
Days Served	-0.00001***	-0.00000	-0.00001***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Days Served Squared	0.00000***	-0.00000	0.00000**	0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Black	0.00063**	0.00203	0.00044	0.00015
	(0.00031)	(0.00145)	(0.00039)	(0.00040)
Hispanic	0.00017	0.00035	0.00042	-0.00060*
	(0.00042)	(0.00099)	(0.00048)	(0.00032)
Other Race	0.00074*	0.00230	0.00072	0.00118**
	(0.00042)	(0.00171)	(0.00071)	(0.00055)
Observations	1714551	143836	797918	1156426
Mean Misconducts	0.00381	0.00322	0.00420	0.00399
Prisoner Controls	Yes	Yes	Yes	Yes
Facility × Month FE	Yes	Yes	Yes	Yes
Facility × Day-of-Week FE	Yes	Yes	Yes	Yes

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering at the facility-month level and are reported in parentheses. Only prisoner-review cycles in which a prisoner experienced at least 89 days both before and after a review are used to estimate these results. Shortened review cycles occur due to prisoner release.

FIGURE 3.7. Prisoner Misconducts in the Days Immediately Adjacent to a Review



Notes: Each point represents the days-from-review fixed effect estimate for days ranging from 15 days before a review to 15 days after, as per equation (3.5). The tails of each point estimate represent the 95-percent confidence intervals, allowing for clustering at the facility-month level.

<u>Short-term responses to assessment</u>

To isolate the short-term misconduct effect of evaluation from other factors, we follow Stephens (2003) and Evans and Moore (2011) in estimating an econometric model similar to (3.3) but with additional flexibility on either side of the evaluation day. That is, allowing for greater flexibility in the days around the threshold itself, we model,

$$M_{dap} \quad = \quad \alpha + \beta_d \sum_{d=-15}^{15} DFA_{dap} + \delta X_{dap} + \mu_{dap}, \tag{3.5}$$

where we allow for separate intercept shifters, β_d, for each day within 15 days of review. Thus, each of the 31 $\hat{\beta}_d$ identify the degree to which rates of misconduct on day d differ systematically from those in the $[-89, -16]$ and $[16, 89]$ ranges. As in previous models, we also include flexible prisoner and time controls as well as facility fixed effects.

In Figure 3.7 we plot all β_d estimates from (3.5) for both prisoners eligible for sentence reductions and those who are ineligible. This has the potential to reveal any empirical regularity in misconduct rates not attributable to controls. These figures therefore reveal day-specific departures from the estimated means on each side of the assessment and, consistent with Table 3.19, there does not appear to be a general decrease in misconducts leading up to the assessment. On the other hand, both panels of Figure 3.7, reveal two days on which there are significant improvements in behaviour: the days immediately before and after assessment.

This improvement in behavior on the day prior to assessment is consistent with models of inmate myopia. This has been observed in other settings, with McCrary and Lee (2009) finding evidence that teens show relatively small responses to the increase in punishments arising when individuals reach adulthood. Such a response however would remain consistent with a Beckerian model of crime, with some individuals exhibiting quasi-hyperbolic discounting. However, there is also a disproportionate decrease in misconducts the day following an assessment, which is not predicted in models of deterrence. It is instead consistent with models of reinforcement, where success at an assessment may temporarily encourage inmates to continue their improved behavior.[19] That said, if this type of reinforcement is driving the reduction in misconducts following assessment, the effect appears to be short lived.

We divide prisoners into their crime type based groups in Figure 3.8. Surprisingly, group A prisoners, despite being ineligible for sentence reductions, show one of the strongest responses to reviews. A possible explanations for this behavior is that the much higher base rate of misconducts among group A prisoners allows for more significant reductions in the number of misconducts committed each day. This result may also be consistent with a reinforcement model where a positive review, even with limited tangible reward, is sufficiently motivating for long term prisoners that they avoid misconducts in the days immediately surrounding a review.

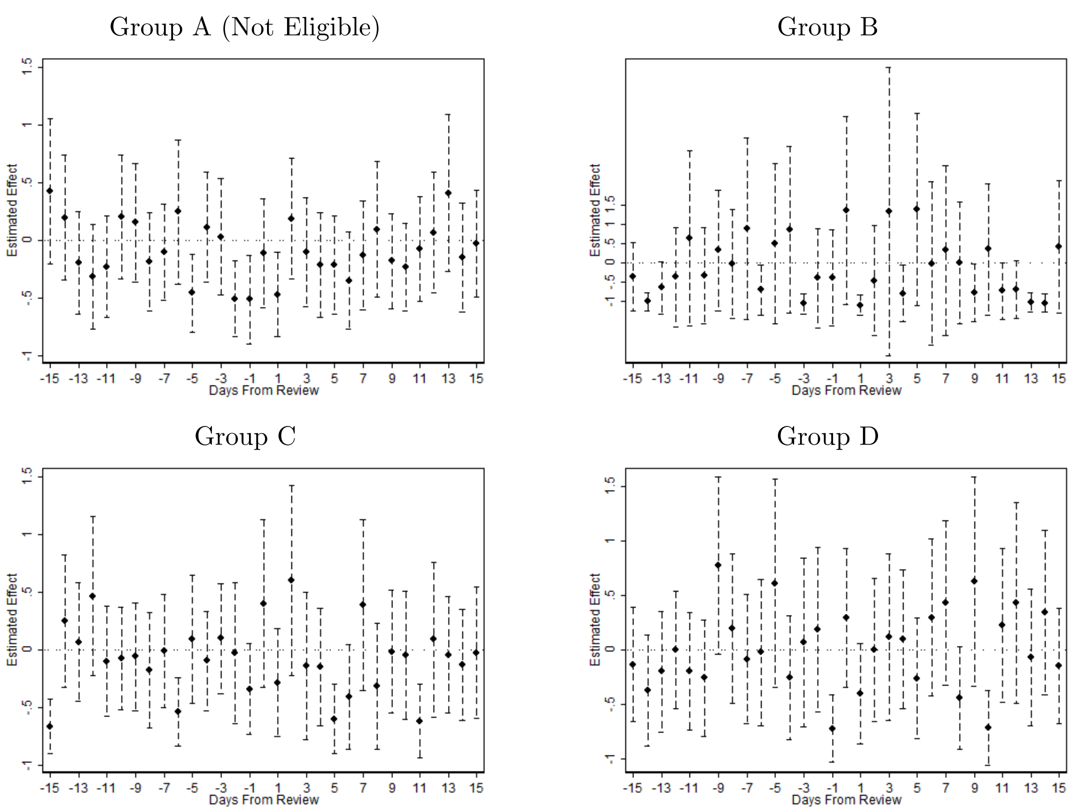
In summary, the results suggest that prisoners show signs of responding to assessment cycles consistent with models of deterrence. We find particular improvements in inmate behavior in the (single) day immediately following an assessment, suggesting that other behavioral elements are in play beyond deterrence.

Conclusion

In this paper we analyze the responsiveness of prisoners to specific behavioral incentives. In order to accomplish this, we first consider the behavior of similar inmates assigned different sentence reduction regimes (20% or 30%) based on the date on which they committed their crime. Allowing for variation in both the intensive and extensive margins, we find no evidence

[19] Given that misconducts in prison are rare events, occurring on only 0.3 percent of prisoner days, 90 percent of prisoner-review cycles result in a full award of sentence reductions. Among prisoners who are penalized in a review we see a similar drop off in misconducts on the day immediately following the review. This may be the result of short term penalties that limit misconduct opportunities for prisoners (e.g., solitary confinement). Conversely, it may suggest that the short term behavioral improvement resulting from an evaluation does not depend on the evaluation resulting in maximum sentence reductions.

FIGURE 3.8. Prisoner Misconducts in the Days Immediately Adjacent to a Review - By Group



Notes: Each point represents the days-from-review fixed effect estimate for days ranging from 15 days before a review to 15 days after, as per equation (3.5). The tails of each point estimate represent the 95-percent confidence intervals, allowing for clustering at the facility-month level.

that prisoners commit fewer misconducts when given the opportunity to serve a smaller fraction of their sentence. We go on to explore heterogeneity on a number of margins including age, recidivism risk, education level, race, and the portion of a sentence that has been served. In each case, we fail to find evidence of a change in prisoner behavior.

We go on to consider the impact of the review cycles used to assign sentence reductions to prisoners. Specifically, we examine how inmates respond to the discontinuous change in incentives arising at the end (and beginning) of regular and repeating assessment periods. When considering the entire review cycle, we again find no evidence that variation in incentives to behave well induce misconduct reductions. On the other hand, prisoners do appear to improve their behavior on the days immediately adjacent to a review. While the improvement leading up to a review is consistent with a Beckerian model of deterrence (given significant myopia), the behavioral improvement following a review is more likely due to reinforcement effects.

The limited impact of the sentence reduction policy changes in Oregon prisons may suggest that 20% sentence reductions are sufficient to achieve the behavioral improvements among prisoners they are partially designed to achieve. On the other hand, it may be the case that the probability of losing sentence reductions is simply too small to motivate prisoner behavior. Recall, in only seven percent of prisoner review cycles do we observe prisoners losing time based on a misconduct. Furthermore, while total sentence reductions were increased from 20% to 30%, half of of those reductions are based on attendance of mandatory programming. This implies the increased incentive to avoid misconducts was a more modest change in terms of actual time served, from 10% to 15%. Said another way, within a single review cycle, the cost of a major misconduct is at most 18 additional days served for a prisoner eligible for 20% reductions and 27 additional days for a prisoner eligible for 30%. Given the high discount rates observed among prisoners, a 9 day reduction in sentence length that is not realized until the prisoner is released may not be sufficiently motivating for prisoners to cause changes in behavior.

Finally, it is important to consider whether the behavioral changes we observe within prison translate into behavior outside of corrections. That is to say, we do not know if prisoners who are less incentivized to behave well while in prison are more likely to commit crimes once released. Whether the generosity of sentence reductions is effective in reducing the criminogenic effects of incarceration is also an important consideration, as is an understanding the of implications that these policy changes have on recidivism.

CHAPTER IV

COMMUNICATION TECHNOLOGY AND VISITATION IN PRISON

This chapter is a component part of co-authored work with Glen R. Waddell and Benjamin Hansen in which I am a full participant.

Introduction

Rates of incarceration are higher in the United States than in any other country—719 prisoners per 100,000 in 2013. Inclusive of those on probation or parole, there are upwards of 7.5 million individuals currently within the correctional population in the United States, with roughly 2 million incarcerated.[1] While recent years have seen some stabilization, or even declines, attenuating a four-decade-long increase in incarceration has proven challenging, leaving policy makers pressed to bring the era of mass incarceration to an end.

This paper lies at the intersection of technological innovation and a broader research agenda on the criminogenic effects of incarceration. There are many moving pieces contributing to outcomes, of course, and identification is challenging in this environment. With administrative data from the Oregon Department of Corrections, we exploit several technology shocks that occurred within the prison system, each introducing exogenous changes in prisoners' marginal costs of communicating with outside family, friends, and support structures.

These shocks come from four distinct sources. First, we exploit a one-time, system-wide change in the per-minute costs associated with telephone communication. Second, we assess a similar one time price shock to a recently introduced video visitation system, similar to Skype of Facetime, which enabled prisoners to not only speak directly with family and friends, but also to potentially increase the intimacy of those communications with the addition of video. While we interpret both sources of variation as shocks to the price of communication, the price change in video conferencing is particularly interesting to us, as we anticipate that this new technology

[1] "Highest to Lowest - Prison Population Total" International Centre for Prison Studies

introduces a closer substitute for in-person visits, the response to which we will be interested in tracking.[2] Finally, we explore the impact of the introduction of two communication technologies that had not previously been available to prisoners, messaging and video chatting.

With the wide variety of technological innovations being introduced more broadly—innovation is apparent from law-enforcement through to incarceration and rehabilitation practices—it is arguable that we are at the margin of a major change in the praxis of criminal justice in the United States, with the potential to guide policy in profound ways.[3] Were there ever an area where informed policy "mattered," the appropriate stewardship of the imprisoned would compete well for such a place. More specifically, the impact of communication with the outside world among the incarcerated population is a key empirical question that has received limited attention in the economic literature.

Allowing prisoners to communicate using technology likely also reduces the cost of prison operations. First, under the current system, in-person visits are free to prisoners (in the sense that neither prisoners nor their visitors pay a fee) yet impose significant costs on the prison.[4] Technology based communication, on the other hand, carries direct costs to the prisoners in the form of service fees. These fees allow the communication provider to provide communication services to the prison without affecting prison budgets. Despite the fees, technology-based

[2]For a editorial on the introduction of video chatting in prisons and the potential benefits it offers both to prisoners and their families, see "A Service to Families and Children." by D. Phillips, Feb. 23, 2014, New York Times. Accessed March 10, 2014. (http://www.nytimes.com/roomfordebate/2014/02/23/does-video-visitation-help-prisons-and-families/video-visitation-protects-children-of-prisoners)

[3]Historically, technology shocks have included forensic innovations such as finger printing, blood type, and ballistics. The introduction of home monitoring has also offered an alternative to incarceration (Renzema and Mayo-Wilson, 2005; Gainey, Payne, and O'Toole, 2000). More recently, New York and other cities are considering the adoption of sophisticated gunshot-locating devices (Choi, Librett, and Collins, 2014). Likewise, expansions of DNA databases may both deter crime and increase the probability of convicting and incapacitating criminals (Doleac, 2012). While the role technology plays in the lives of those already incarcerated has not been widely studied, there is some evidence that prisoners are acceptive of receiving medical consultations via video conference (Mekhjian, Turner, Gailiun, and Mccain, 1999).

[4]For example, in-person visitation requires extra guards to process visitors and monitor interactions.

communication is also cheaper for prisoner's families who can now avoid the gas costs and possibly hotel stays inherent in visiting prisoners incarcerated across the state.[5]

While there is some evidence that restricting prisoner communication by allowing only postcards through the prison mail system reduces the probability of successful rehabilitation into a community (Sakala, 2013), no robust quantitative studies have assessed the potential benefits of telephone and video communication for inmates and the extent to which they interact with in-person visitation of prisoners. Hilliman (2006) explores how the introduction of video conferencing technology that allowed incarcerated mothers to communicate with their children affected a treatment group of 335 women over the course of 18 months. She found no change in misconduct rates although the women reported increased self-esteem. Similarly, White, Galietta, and Escobar (2006) interviewed 36 incarcerated mothers in Connecticut and concluded the women placed a high value on the availability of VIP services.

Results analyzing the impact of increased communication on recidivism and misconduct rates are more consistent and suggest that increased visitation may be associated with reduced rates of recidivism (Duwe and Clark, 2013) and with lower levels of prisoner misconduct (Siennick, Mears, and Bales, 2013; Cochran, 2012), at least in the short-run.[6] While these studies are suggestive, the causal relationship between in-person visits and outcomes has not been well established due to the lack of exogenous variation and significant evidence that the prisoners being visited are different on a number of margins than those that are not (Cochran, Mears, and Bales, 2014). Moreover, to the extent telephone and video communication crowd out in-person visits—an important substitution effect—any benefits delivered through lower communication costs may be offset by reductions in "net" visitation. Thus, we investigate the effects of these policy changes on prisoner visitation.

[5]The costs of travelling to visit loved ones in prison are occasionally substantial enough that families choose to move close to the prison after incarceration.

[6]There is an extensive criminology literature on the link between family ties, visitation, and recidivism. Some of the key papers include Bales and Mears (2008); La Vigne, Naser, Brooks, and Castro (2005); and Cobbina, Huebner, and Berg (2012). In addition, Segrin and Flora (2001) explore the effects of limited communication with spouses during incarceration

Furthermore, previous research suggests longer distances to home increase recidivism, as do higher security prisons (Drago, Galbiati, and Vertova, 2011; Chen and Shapiro, 2007). To the extent that these results are driven by the isolation experienced by prisoners and their separation from the outside world, increased communication opportunities may have significant impacts on future recidivism. Related to these issues, we investigate policy changes in Oregon which reduced the degree of isolation experienced by the incarcerated.

We find no evidence that technology based forms of communication lead to substitution away from in-person visitation overall although in-person visitation at prisons located far from population centers may suffer. Total communication appears to have increased in all facilities, regardless of location, with certain groups of prisoners, including women and prisoners under the age of 43 adopting the technologies more quickly and communicating more frequently.

The remainder of the paper proceeds as follows. Section 4.2 provides background on the institutions and the policy changes in Oregon. Section 4.3 discusses the administrative data sources, while Section 4.4 discuses econometric models and Section 4.5 results. Section 4.6 concludes.

Background

On July 1, 2012 the Oregon Department of Corrections changed phone service providers to Telmate. At that time, inmates were offered a new menu of prices for their communication with the outside world. Prior to Telmate's introduction, calls carried a fixed costs in addition to a relatively low per-minute rate. Telmate removed the flat rates associated with making a call and instead offered prisoners a higher per minute rate. All else equal, prisoners are thus expected to make more phone calls after the price change, but average call duration should fall.[7]

[7] The direction of these changes is reinforced by Telmate's policy of offering each prisoner one free three-minute call to each of their up to ten preferred numbers each month.

TABLE 4.1. Long Distance Rates

	Prior to 7/01/2012		Post 7/01/2012		Percent Increase	
	Collect	Debit	Collect	Debit	Collect	Debit
Local 10 minute call	2.64	1.75	1.30	0.85	-68	-69
Local 20 minute call	2.64	1.75	2.60	1.70	-2	-3
Local 30 minute call	2.64	1.75	3.90	2.55	39	37
In state 10 minute call	10.85	6.85	1.70	1.50	-105	-128
In state 20 minute call	17.75	11.35	3.40	3.00	-136	-116
In state 30 minute call	24.65	15.85	5.10	4.50	-131	-112
Out of state 10 minute call	12.85	7.85	6.50	4.00	-66	-65
Out of state 20 minute call	21.75	13.35	13.00	8.00	-50	-50
Out of state 30 minute call	30.65	18.85	19.50	12.00	-44	-44

Notes: Note: percent changes calculated using the midpoint method. The mean duration of phone calls in our sample was 13 minutes. The call duration distribution takes on a bimodal distribution with both short calls (less than 5 minutes) and long calls (more than 25 minutes) more common than intermediate call lengths.

In Table 4.1 we report the total cost of calls for a variety of locations and call lengths before and after the price changes.[8] Table 4.1 clearly indicates the switch to Telmate represented a remarkable shift in the cost of communications for inmates. Unfortunately, observing whether an individual is paying local or long-distance rates on a given call is not possible. Some prisoners' families (presumably those with the greatest call volume) reportedly purchased cell phones with numbers local to prison so that they could pay local rates from anywhere.[9] Furthermore, while we have been able to acquire phone use data from Telmate, no matching set is available from the previous provider making a direct comparison of phone use before and after the change impossible.

This large shift in prices for Oregon correctional facilities actually preceded nationwide shifts in the costs of communication for inmates. In most settings, the state department of corrections grants a single communications provider a monopoly contract to serve all prisons within the state. The resulting market power—supported further by the need for all communication from inmates to those outside of the system to be closely monitored—has lead

[8]Most prisons in the Oregon system cap call lengths at 30 minutes. Approximately 8% of phone calls reached this length limit.

[9]Aggregate data suggests that this was becoming a significant problem for the DOC's previous phone provider with the fraction of local calls increasing from 38% in 2007 to 70% in 2012. As a result, phone revenue fell each year from 2007-2012 even as the total prison population increased.

to those providers charging very high per-minute rates to inmates. While already somewhat controversial, these contracts became so lucrative in recent years that providers had begun to compete for the service agreements with larger and larger payments to prison systems (Zimmerman and Flaherty, 2007). Allegations of unfairly high prices and poor service are not uncommon, and the potential for rising demand for black market communication caused the Federal Communication Commission (FCC) to cap per-minute phone rates at $0.25 per minute in August 2013 (The lower prices took effect nationwide on February 11, 2014).[10] Given that the Oregon price changes preceded the nationwide caps, this study offers a unique quasi-experiment that allows us to better predict the impact of similar policy shifts occurring all over the nation.[11]

In addition to lowering per-minute phone rates, Telmate also introduced both text messaging and video chat technologies to Oregon prisons. The messaging service came online July 23, 2013 and allowed prisoners to send and receive text messages to contacts outside of the prison. Each text costs a prisoner $0.44 and is read by a specially trained guard who determines whether the message contains any prohibited information before sending it on the the intended recipient if the message passes inspection.[12] Most commonly, messages are "flagged" and not forwarded when they are suspected of containing code words designed to facilitate the smuggling of drugs or other contraband into the prison. Prisoners have two methods by which they can send and receive texts. All prisoners have access to kiosks stationed around the prison facility. At these kiosks, prisoners can log into their personal accounts and type messages to send. Messages received by prisoners using this system are printed and a physical copy are given to the inmate.

[10] Kang, C. "FCC to Vote on Lowering Prison Phone Call Rates." Washington Post. 8/8/2013. http://www.washingtonpost.com/business/technology/2013/08/08/e170a1f8-ff8e-11e2-9711-3708310f6f4d_story.html

[11] An overview of the history of prison phone rates and the motivations for the FCC's actions can be found in Downs (2014).

[12] We are not able to observe which party pays for any form of communication. All forms of communication are billed to each prisoner's account. The prisoner can earn money for this account through work programs and family and friends can contribute money to it for a small fee. Anecdotal evidence suggests many prisoners, and especially those frequently using communication technology or receiving visits, receive significant wealth transfers from friends and family on the outside.

Video chatting supplements traditional phone calls by allowing prisoners to experience live, two-way video during the call. These calls take place at special stations located throughout the prison and every session is monitored. While video chatting is closer to in-person visitation than phone conversations, there is a noticeable delay imposed in each direction. This allows for the individuals monitoring the conversation to cut the feed and prevent any prohibited topics from being discussed. VIP services were introduced across prison facilities over time. In Table 4.2 we report the dates on which VIP was made available at each prison. Originally, VIP sessions cost $20 for a 30 minute call. On November 1, 2013 the price was permanently reduced to $9.90 per call.[13] We can identify the effects of selection into VIP services by separately considering prisoners who were using the service before the price change, those who began using the service only after the price change, and prisoners who never used the service at all.[14] Other states across the nation are also considering video chatting and some have already made it available. This includes Indiana, Ohio, Pennsylvania, Virginia, and Washington. Several other states have also implemented on-site video chatting as alternative to in-person physical visits as well.[15]

Of course, each of the technology introductions and price changes detailed above also changed the relative prices of other types of communication. For example, as the cost of phone calls decreased, in-person visitation became relatively more expensive as a means to communicate with the outside world. On the other hand, there may be significant income effects associated with reducing the price of phone calls. This is particularly relevant in prison settings where much of the money used to pay for communication is deposited by family members outside

[13]Originally this price cut was intended to only last for the Holiday season, returning to $20 per call on February 1, 2014. Prisoners were not made aware the price decrease was to be made permanent until February 1. We observe a significant decrease in the number of VIP sessions taking place after February 1, 2014. It is likely that the belief that the price change was temporary introduced a harvesting effect that both increased VIP sessions before February 1, 2014 and decreased them after the threshold.

[14]Two facilities, OSP and OSCI, did not have VIP availability until after the price change on November 1, 2013. As such, these prisons are omitted from our analysis of the effect of the VIP price change.

[15]Telmate also introduced a delayed text messaging service that allowed prisoners to send and receive short messages using kiosks placed in each prison. Messaging became available for purchase on September 13, 2012 and message use gradually increased from that date forward. We assess how the use of these messages changed after the VIP price decrease occurred in the results section.

TABLE 4.2. Video-Chat Rollout

Date	Facility	Abbreviation	Daily Prisoners
31 October 2012	Snake River Correctional Institution	SRCI	2315
1 November 2012	Warner Creek Correctional Facility	WCCF	372
11 November 2012	Coffee Creek Correctional Facility	CCCF	1178
4 March 2013	Columbia River Correctional Institution	CRCI	390
4 March 2013	Mill Creek Correctional Institution	MCCF	202
5 March 2013	Santiam Correction Institution	SCI	314
5 March 2013	Powder River Correctional Facility	PRCF	227
6 March 2013	Deer Ridge Correctional Institution	DRCI	542
7 March 2013	Shutter Creek Correctional Institution	SCCI	213
7 March 2013	South Fork Forest Camp	SFFC	155
20 March 2013	Eastern Oregon Correctional Institution	EOCI	1438
16 July 2013	Two Rivers Correction Institution	TRCI	1447
6 November 2013	Oregon State Penitentiary	OSP	1574
5 December 2013	Oregon State Correctional Institution	OSCI	621

of prison. In the aftermath of price reductions in either phone calls or VIP services, families may find they can contribute less to the prisoner's communication budget freeing up money for visitation. It is also possible that families would instead choose to continue to contribute money to the prisoner's account at the same rate. In this case, a price decrease would give the prisoner additional opportunities to use any form of communication available. Again, this would suggest a price decrease for one type of communication could lead to an increase in usage of other forms of communication ever though they are now relatively more expensive.

A number of papers have condsidered how communication technologies may effect the need for face-to-face interactions and, by extension, cities. Gaspar and Glaeser (1998) consider the advent of internet based communication and find that rather than acting as substitutes, internet based communication causes individuals to choose to make more contacts. Overall, this appears to increase demand for face-to-face interactions. Similalry, Leamer and Storper (2001) recognize that the interent will allow for digital transimission of certain information that previously required in-person interaction but will also increase the complexity of productive activity making communciation more important. The authors argue this need for increased communication will more than offset any potential substitution effects. If similar patterns hold in a prison setting, these results suggest that introducing new communication technologies and reducing the prices on existing technologies may lead to increased demand for in-person visitation even as communication companies argue in-person visitation is no longer neccesary given the technology based communication options prisoners have available.[16]

Data

In order to speak to the responsiveness of in-person prisoner visitation to cheaper video-chat technology, we utilize rich administrative records of the Oregon Department of Corrections. We study the universe of adult male prisoners from July 1, 2009 to March 31, 2015.[17]

Prisons are divided into rural and urban based on whether they are located in a city of more than 10,000 people.[18] This designation is meaningful because all urban prisons lie along the main interstate in Oregon and within a few hours of the three largest population centers in Oregon (i.e., Portland, Eugene/Springfield, and Salem). All rural prisons lie off of the Interstate-5 corridor. The exact locations of each prison can be found in Figure 4.1.[19]

We supplement the Oregon DOC data with data from the U.S. Energy Information Administration (EIA), capturing weekly gasoline prices. Driving distances and times were calculated using Mapquest.[20] We assume that visitors were traveling from the centroid of the county in which the prisoner was convicted to the address of the prison currently holding the prisoner. Prisoners are assigned to prison based on the severity of their crime and where beds are available. The county in which a prisoner commits a crime does not affect where they serve their sentence. In addition, we include county level daily temperature and precipitation data from the

[16] Some prison communication companies that offer video visitation actually require in-person visits to be elimitated (Stroud and Brustein, 2015).

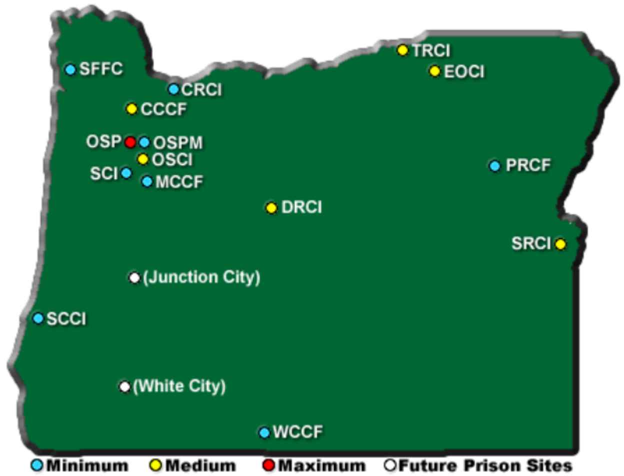
[17] We exclude prisoners who were not convicted in the state of Oregon. This group makes up less than 1% of the entire sample.

[18] In practice this distinction is very clear cut, the largest town containing a rural prison has a population of 9,872 while the smallest city containing an urban prison has more than 100,000 people.

[19] Map created by the Oregon Department of Corrections. It is available at *http://www.oregon.gov/doc/*

[20] John Voorheis created an an ado file automating the linkage to mapquest data.

FIGURE 4.1. Oregon Prison Locations



National Oceanic and Atmospheric Administration in order to better understand the full costs of physically visiting a prisoner on a given day.

Table 4.3 presents summary statistics with variables presented at both the prisoner-day and prisoner level. Column 1 includes all prisoners in Oregon while subsequent columns narrow this sample to prisoners increasingly likely to benefit from price reductions in communication technologies. Specifically, Column 2 includes only those prisoners who make at least one phone call during their sentence, Column 3 indicates mean values among prisoners who used VIP chat services at least once during their sentence, and Column 4 includes only those prisoners who used VIP chatting before November 1, 2013 when the price of that service was reduced.[21]

On a given day in the Oregon Prison System, roughly 2.4 percent of the population receives at least one visitor.[22] Conditional on receiving at least one visitor a prisoner's expected value for visitors is 1.8. Even among prisoners who were early adopters of the VIP chat system, phone calls and in-person visitation remain the dominant forms of communication with the outside world.

[21]Some care should be taken in cross group comparisons. Prisoners in columns 3 and 4 must have been released after VIP introduction in their prison to be included in this sub-sample. There is thus both a behavioral and a time based selection process leading to differences between groups.

[22]The visitation statistic is somewhat misleading as most facilities only offer visitation a few days each week. Conditional on visits being allowed, the visitation rate increases to 3.6 percent.

TABLE 4.3. Summary Statistics

	All Prisoners	Ever Make Phone Call	Ever Use VIP	Early Adopt VIP
Prisoner-Day Level Summary Statistics				
VIP Sessions	0.0016	0.0021	0.0063	0.0076
Messages Sent	0.0048	0.0064	0.0157	0.0130
Messages Received	0.0047	0.0063	0.0157	0.0130
Total Visits	0.0431	0.0440	0.0559	0.0649
Family Visits	0.0297	0.0308	0.0380	0.0444
Friend Visits	0.0099	0.0097	0.0129	0.0150
Phone Calls Made	0.1404	0.1873	0.2823	0.2896
Phone Call Duration	12.96	12.96	13.15	13.62
Gas Price	3.44	3.50	3.50	3.52
Temperature	52.04	52.09	52.16	52.03
Precipitation	0.0970	0.0961	0.0966	0.0965
Days Served	1311.65	1330.13	1345.03	1478.38
Observations	21,434,240	16,071,088	5,403,288	2,649,083
Prisoner Level Summary Statistics				
Total Crimes	2.54	2.76	3.23	3.49
Violent Crimes	0.59	0.67	0.91	1.03
Sentence Length	3199.23	3892.89	5354.78	6079.94
Age	36.96	35.68	32.84	33.61
White	0.74	0.75	0.73	0.72
Black	0.09	0.09	0.11	0.11
Hispanic	0.13	0.13	0.12	0.13
Other Race	0.04	0.04	0.04	0.05
ACRS Score	0.22	0.21	0.19	0.16
Recidivists	0.28	0.27	0.26	0.26
Parole Violators	0.14	0.12	0.12	0.12
Prisoners	33,9251	21,151	5,576	2,090

Notes: Phone call duration is conditional on at least one call being made on that day.

Empirical Model

An in-person visit is the coincident behaviors of both the prisoner and visitor, with prisoners first consenting to receive each individual visitor prior to receiving them. Several factors influence the likelihood of visitation in addition to the policy changes we are studying. These factors include distance travelled, gas prices, the age of inmate, race, criminal history, the nature of the convicted offense, the fraction of the sentence served, seasonality, weekends, holidays, weather, and factors specific to every facility (such as the security level and geographic isolation not captured by the distance measure). We therefore model in-person visits, V, as

$$\begin{aligned} Visits_{pfd} = \beta_0 + \beta_1 CheapVIP_d + \beta_2 Date_d + \beta_3 CheapVIP * Date_d \\ + \gamma_1 X'_{fd} + \gamma_2 Z'_p + \delta_f + \epsilon_{pfd} \end{aligned} \tag{4.1}$$

where $Visits_{pfd}$ is a count variable capturing the number of visits prisoner p receives while in facility f on day d. $CheapVIP_d$ captures the policy variation described above, with $CheapVIP_d$ varying only in time. In particular, $CheapVIP_d = 1$ anytime on or following treatment. We include flexible time trends before and after treatment in $Date_d$ and $CheapVIP * Date_d$.

In X_{fd}, we control for gasoline prices, weather, distance, weekends and holidays while in Z_p we control for prisoner level characteristics.[23] d_{fd} represents a faciliy by day-of-week fixed effect which cotrols for both facility specific traits and days at each facility when in-person visitation is not allowed. ϵ_{pfd} captures the error term. In all specifications, we correct for possible clustering

[23] On holidays, prisons can open for visitation when they normally would not be. If a holiday falls on a day when visits were already allowed, however, prisons tend to grant "holiday" hours on the day before or the day after the actual holiday. Prisoner level characteristics include dummy variables indicating the number of total and violent crime the prisoner has been convicted of, a months served fixed effect, decile bins for age and sentence length, race dummies, and a crime type fixed effect that inlcludes ten categories (violent, drug, theft, sex, child sex, vandalism, parole violations, gun related, whitecollar, and other).

in the residuals by date. We also estimate models with and without controls. Similar models are used to estimate all other outcomes of interest including VIP use, phone calls, and messaging.

Results

VIP Price Change

We begin by assessing the VIP price change which offers a clearer picture of the real impact on the price of that service for the average prisoner and more complete data about usage of the various communication tools prisoners have at their disposal. Throughout our analysis of the VIP price change, we exclude two facilities, Oregon State Penetentiary (OSP) and Oregon State Correction Institute (OSCI). These intsitutions did not have VIP services available unitl shortly after the price change. As such, including them would introduce the potential for the introduction of VIP services to be driving our results rather than the price change.

As a first stage, Figure 4.2 shows the change in VIP usage before and after the price change. The large spikes seen in usage are an artifact of the policy being implemented on November 1^{rst}. As such, the period immediately following implementation includes high use during holidays such as Thanskgiving, Christmas, and New Years. Surprisingly, despite the clear increase in VIP usage seen in the figure, in Table 4.4, which presents estimates of our preferred specification (equation 4.1) across a number of prisoner groups based on their usage of communication technologies, we do not find a statistically significant increase in VIP use after treatment. The coefficient estimates suggest an economically large shift in usage, with VIP chats increasing by 50% in the first three columns and by 60% among prisoners who started using VIP services before the price decrease. Even among this group, however, VIP sessions appear to be too rare for a statistically significant effect to be found.

The next issue of interest is to determine whether increased communication availability had a discernible effect on visitation and other forms of communication. Theoretically, the question is whether or not video chatting is used as a substitute for in-person visits and other

FIGURE 4.2. VIP Use Before and After November 1, 2013

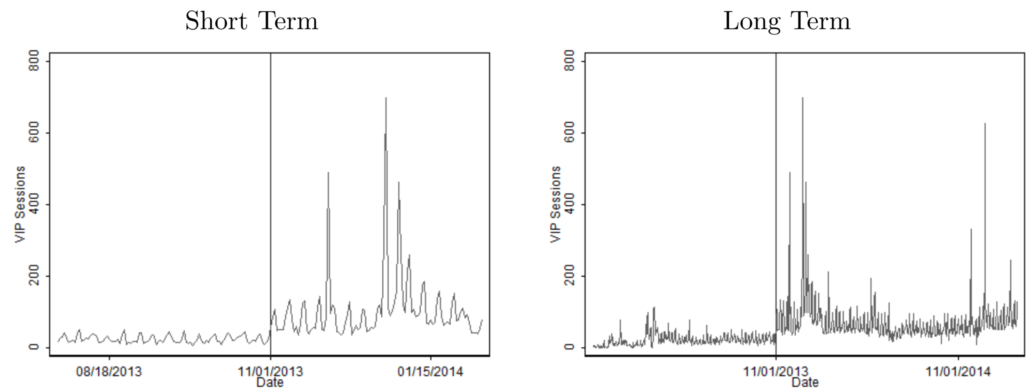


TABLE 4.4. VIP Price Change - Change in VIP Usage

	(1)	(2)	(3)	(4)
Treat (=1 if after 11/1/2013)	0.00087	0.00094	0.00258	0.00622
	(0.00114)	(0.00123)	(0.00308)	(0.00461)
Date	0.01214**	0.01298**	0.03230**	0.04351**
	(0.00481)	(0.00517)	(0.01302)	(0.01911)
Date^2	0.00437**	0.00472**	0.01166*	0.01664**
	(0.00220)	(0.00237)	(0.00597)	(0.00835)
Date*Treat	0.02077***	0.02243***	0.05451***	0.05512**
	(0.00636)	(0.00687)	(0.01699)	(0.02454)
Date^2*Treat	-0.03418***	-0.03679***	-0.09064***	-0.11272***
	(0.00796)	(0.00858)	(0.02126)	(0.03135)
Weekend	0.00260***	0.00353***	0.00825***	0.01760***
	(0.00089)	(0.00096)	(0.00221)	(0.00327)
Holiday	0.01554***	0.01674***	0.04192***	0.06067**
	(0.00593)	(0.00638)	(0.01590)	(0.02420)
Observations	2,119,832	1,961,720	773,808	360,329
Mean	0.00184	0.00198	0.00517	0.01046
Weather and Gas Price Controls	Yes	Yes	Yes	Yes
Prisoner Controls	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth. Two facilities did not have access to VIP services until after the price change on November 1, 2013. These facilities our excluded from this analysis. Each column restricts the included sample to prisoners using the technology indicated in the column heading. VIP Early Adopters are those prisoners using VIP services before the price change.

forms of communication. The price change also represents a small but potentially important income effect. For frequent users of VIP services, a price reduction may allow for greater use of other communication technologies including in-person visitation. Finally, there may be strong relationship maintenance effects through which a prisoner's ability to be more involved in the lives of family and friends from afar could lead to increased visitation and other forms of communication.

Figure 4.3 displays messaging, phone calls, and vitiation in the 100 days before and after the VIP price change. Each variable has been demeaned by day-of-week. Neither phone calls nor total visits appear to be directly affected by the VIP price change. While this may seem surprising, recall that VIP chats are far less common than either visits or phone calls with the majority of prisoners never using VIP services during their incarceration. Unlike the other forms of communication, visitation shows significant valleys in addition to the holiday peaks. These valleys are the result of significant weather evens in Oregon during the period that increased the cost of travelling. Messaging use, and particularly messages sent, does appear to increase. Interestingly, the increase in messages sent appears to slightly precede the VIP price reduction. One potential explanation for this is that prisoners use messaging technology to coordinate and facilitate the higher cost methods of communication.

Table 4.5 reports estimates for the effect of introducing cheaper video chat on in-person visitation in the 100 days leading up to and follwoing the price change. Column 1 estimates a basic model which adjusts for monthly seasonality and includes controls for weekends and holidays. Column 2 adds controls for weather, gas prices, distance from home county to the prison, and prisoner characteristics. Column 3 adds controls for prisoner characteristics and Column 4 includes a facility by day-of-week fixed effect designed to fully capture the days on which visitation was allowed at each facility.

The coefficient on the key variable of interest, Treat, is postive and insigificant in all columns where we control for weather and distance. While this suggests that predictions of

FIGURE 4.3. Other Communication Use Before and After November 1, 2013

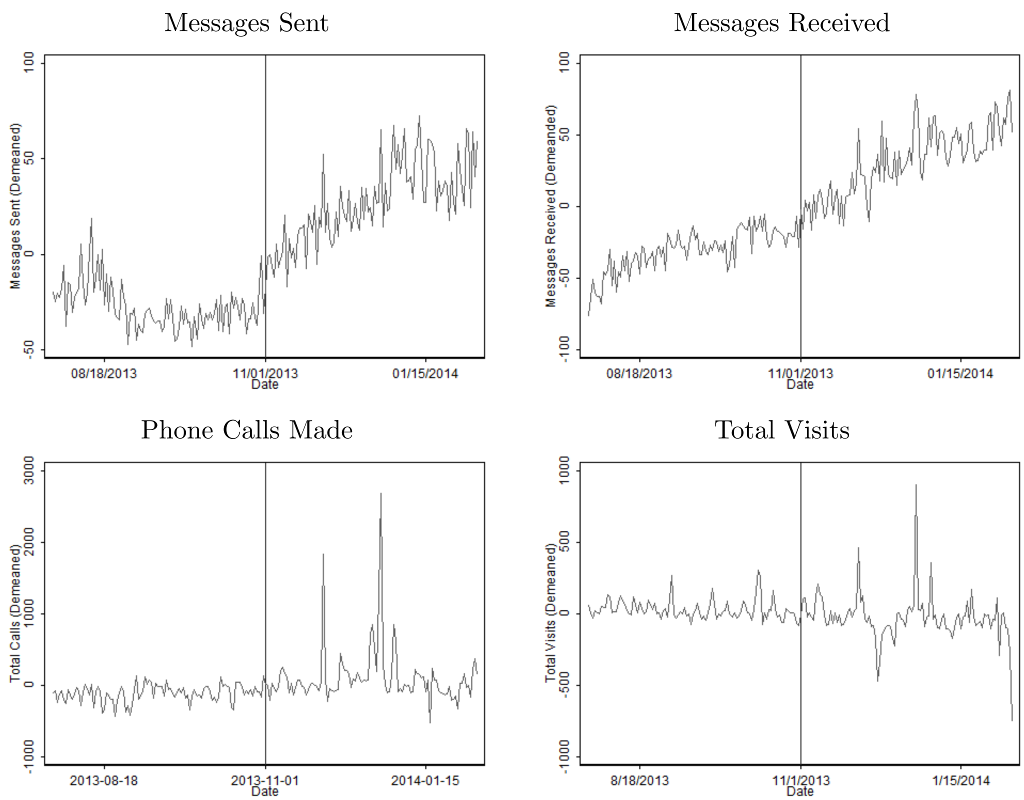


TABLE 4.5. VIP Price Change - Total Visits

	(1)	(2)	(3)	(4)
Treat (=1 if after 11/1/2013)	-0.00258	0.00647	0.00626	0.00291
	(0.00560)	(0.00500)	(0.00500)	(0.00367)
Date	-0.00283	0.07163***	0.07511***	0.06315***
	(0.01421)	(0.02149)	(0.02156)	(0.01589)
Date^2	0.00037	0.01424	0.01604	0.01261
	(0.01324)	(0.01315)	(0.01314)	(0.00764)
Date*Treat	0.01244	-0.02044	-0.02106	-0.01215
	(0.02871)	(0.02315)	(0.02312)	(0.01804)
Date^2*Treat	-0.02457	-0.07130**	-0.07568**	-0.07016***
	(0.03068)	(0.02992)	(0.03007)	(0.02661)
Weekend	0.06658***	0.06586***	0.06578***	0.07618***
	(0.00226)	(0.00195)	(0.00194)	(0.00567)
Holiday	0.03947***	0.03908***	0.03902***	0.03972***
	(0.00994)	(0.01007)	(0.01014)	(0.00990)
Distance		-0.00041***	-0.00045***	-0.00040***
		(0.00003)	(0.00003)	(0.00002)
Distance^2		0.00000***	0.00000***	0.00000***
		(0.00000)	(0.00000)	(0.00000)
Gas Price		0.13799***	0.13931***	0.10831***
		(0.03593)	(0.03614)	(0.02711)
Home County Temperature		0.00005	0.00006	0.00006
		(0.00010)	(0.00010)	(0.00007)
Prison Temperature		0.00021	0.00024*	0.00029***
		(0.00014)	(0.00014)	(0.00008)
Home County Precipitation		-0.05059**	-0.05267**	-0.04750***
		(0.02087)	(0.02083)	(0.01733)
Prison Precipitation		-0.12961***	-0.12462***	-0.09438**
		(0.04175)	(0.04217)	(0.03647)
Home County Temp*Precip		0.00264***	0.00261***	0.00173**
		(0.00078)	(0.00079)	(0.00067)
Prison Temp*Precip		0.00081**	0.00083**	0.00080**
		(0.00039)	(0.00039)	(0.00031)
Black			-0.01046***	-0.01171***
			(0.00107)	(0.00101)
Hispanic			-0.00178**	-0.00182**
			(0.00073)	(0.00084)
Other Race			-0.00704***	-0.00703***
			(0.00118)	(0.00113)
Observations	2119832	2119832	2119832	2119832
Mean	0.04052	0.04052	0.04052	0.04052
Weather/Gas Price Controls	No	Yes	Yes	Yes
Prisoner Controls	No	No	Yes	Yes
Facility*DOW FE	No	No	No	Yes

Notes: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth. Two facilities did not have access to VIP services until after the price change on November 1, 2013. These facilities our excluded from this analysis.

TABLE 4.6. VIP Price Change - Total Visits Among Communication Technology Users

	All Prisoners	Phone Users	VIP Users	VIP Early Adopters
Treat (=1 if after 11/1/2013)	0.00291	0.00314	0.00504	0.00524
	(0.00367)	(0.00398)	(0.00558)	(0.00742)
Date	0.06315***	0.06865***	0.11575***	0.16023***
	(0.01589)	(0.01708)	(0.02450)	(0.000033)
Date^2	0.01261	0.01440*	0.03157**	0.05001***
	(0.00764)	(0.00821)	(0.01322)	(0.01710)
Date*Treat	-0.01215	-0.01433	-0.04263	-0.06746**
	(0.01804)	(0.01953)	(0.02658)	(0.03377)
Date^2*Treat	-0.07016***	-0.07592***	-0.11311***	-0.15271***
	(0.02661)	(0.02859)	(0.03779)	(0.04703)
Weekend	0.07618***	0.09295***	0.10716***	0.15441***
	(0.00567)	(0.00625)	(0.00745)	(0.01226)
Holiday	0.03972***	0.04309***	0.05431***	0.06176***
	(0.00990)	(0.01068)	(0.01207)	(0.01432)
Observations	2,119,832	1,961,720	773,808	360,329
Mean	0.04052	0.04345	0.05584	0.06718
Weather and Gas Price Controls	Yes	Yes	Yes	Yes
Prisoner Controls	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes

Notes: * p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth. Two facilities did not have access to VIP services until after the price change on November 1, 2013. These facilities our excluded from this analysis. Each column restricts the included sample to prisoners using the technology indicated in the column heading. VIP Early Adopters are those prisoners using VIP services before the price change.

significant substitution effects due to VIP sessions are overblown, it may simply be the case that too few prisoners are using VIP services to pick up a statistically significant effect on the population. To explore this possibility, in Table 4.6 we present the results of our preferred specification (Column 4 of Table 4.5) for a variety of sub-samples. Column 1 replicates the results from Table 4.5 for easy comparison while Column 2 includes only those prisoners who made a phone call at some point during their incarceration. While this group is nearly as large as the total population, it conveniently drops the most isolated prisoners allowing us to focus on the group more likely to receive visitors.[24] Columns 3 and 4 assess the impact of the price change on the prisoners who have used VIP chatting technology with Column 4 further restricting this sample to prisoners that took part before the price decrease.

[24]While the cost of phone calls may be a partial detractor for some prisoners, Telmate has had certain days each year where they offer one free call to every prisoner. These days vary some but traditionally include at least Mother's Day and Father's Day. In all specifications, we include a dummy variable equal to one if the Telmate offered free calls on that day.

Across columns, we find no evidence that the price reduction in VIP chatting lead to an immediate increase in visitation. While coefficient estimates do increase as we restrict the sample to prisoners more directly affected by the price change, the mean visitation rates also increase. Ultimately, the percentage impact of the price change remains consistent across groups.

In addition to total visits, a change in the price of one communication technology may lead to significant changes in the usage of other communication technologies. In order to fully understand the potential impacts of the policy change, it is necessary to explore the impact on all forms of communication and allow, where possible, for heterogeneity in responsiveness depending on the prisoner's relationship to their communication partner. Thus, in Table 4.7 we explore a variety of communication types available to prisoners. Specifically, in Columns 1 and 2 we report the effect on family and friend visitation, by far the largest two categories of visitors. Columns 3 and 4 indicate impacts on messages sent and received while Column 5 estimates the effect of the price reduction on phone call use. Finally, Columns 6 presents estimates in which the total communication a prisoner has had, inclusive of VIP sessions, is included as the dependent variable. In each column, we replicate our preferred specification from Table 4.5 including a full set of control variables in addition to facility fixed effects.

With the exception of messaging, no form of communication changed significantly immediately after the VIP price reduction. We estimate total messaging use increased by 18% which appears reasonable given a 50% increase in VIP sessions. We can also consider the implied number of messages required to coordinate a VIP session if we assume that the increase in messaging use was entirely driven by prisoners attempting to coordinate VIP sessions with family and friends on the outside. The evidence suggests the VIP price decrease increased VIP sessions by 0.32 per prisoner-year while messaging increased by 0.89 per prisoner year. This suggests each VIP session requires 2.78 messages to coordinate. Furthermore, because the coefficient on messages sent is roughly double that of messages received. It appears reasonable to conclude

TABLE 4.7. VIP Price Change - Other Communication Measures

	(1) Family Visits	(2) Friend Visits	(3) Messages Sent	(4) Messages Received	(5) Calls	(6) Total
Treat (=1 if after 11/1/2013)	0.00171	0.00076	0.00179***	0.00064*	-0.01054	-0.00433
	(0.00275)	(0.00076)	(0.00048)	(0.00034)	(0.00705)	(0.01007)
Date	0.04480***	0.01404***	0.00669***	-0.00307*	0.00062	0.07954**
	(0.01174)	(0.00345)	(0.00175)	(0.00159)	(0.02630)	(0.03522)
Date^2	0.00913	0.00284*	0.00497***	-0.00560***	0.00327	0.01962
	(0.00580)	(0.00167)	(0.00144)	(0.00109)	(0.01434)	(0.01771)
Date*Treat	-0.00800	-0.00423	0.00490**	0.01111***	0.09137**	0.11601**
	(0.01342)	(0.00366)	(0.00195)	(0.00175)	(0.03525)	(0.04964)
Date^2*Treat	-0.04989***	-0.01475**	-0.01199***	0.00271	-0.09982**	-0.21343***
	(0.01911)	(0.00600)	(0.00221)	(0.00204)	(0.04144)	(0.05925)
Weekend	0.04994***	0.02066***	0.00064	0.00089	0.00975*	0.09005***
	(0.00415)	(0.000146)	(0.00103)	(0.00073)	(0.00555)	(0.00811)
Holiday	0.02853***	0.00855***	0.00065	0.00172***	0.07809**	0.13572***
	(0.00784)	(0.00155)	(0.00070)	(0.00061)	(0.03115)	(0.04763)
Observations	2,119,832	2,119,832	2,119,832	2,119,832	2,119,832	2,119,832
Mean	0.02846	0.00894	0.00750	0.00637	0.28783	0.34407
Weather/Gas Price Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prisoner Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:** p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth. Two facilities did not have access to VIP services until after the price change on November 1, 2013. These facilities our excluded from this analysis. Each column has a unique dependent variable as indicated in the heading of that column. The dependent variable in column 6 is the sum of all forms of communication a prisoner can receive that we observe. Specifications are consistent with column 4 of Table 4.5

prisoners often initiate the communication with a response by the outside party and a final confirmation from the prisoner.[25]

Both phone calls and total communication indicate strong increases in usage over time following the change. This is consistent with prisoners initially responding to the price change with increased VIP use and then gradually expanding their communication patterns into other technologies. Is is also worth noting that the sign on our treatment variable for total communications is negative even though all columns other than phone use are positive. The dominance of phone calls as a communication method is an important result that policy makers should be aware of. Moreover, the prevalence of phone use, even among prisoners who have adopted VIP chatting as a communication method, suggests that changes in phone call pricing may have a much more significant effect on visitation that VIP price changes, even if phone calls are a less similar substitute for visitation.

[25] Emperical evidence suggests that VIP sessions are relatively difficult for prisoners to coordinate. 76% of scheduled VIP sessions do not actually take place.

Telephone Price Change

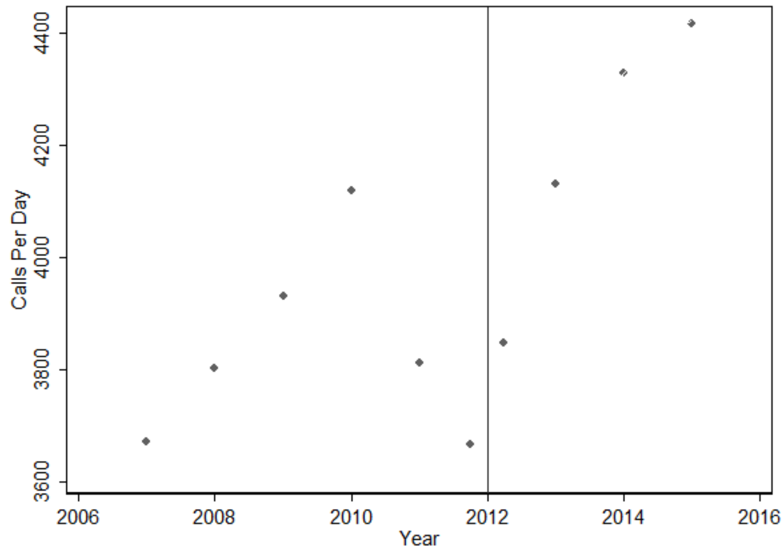
We next apply the model developed for the VIP price decrease to the other major price change that occurred in the Oregon Prison System. Specifically, in this section we explore the impact of the rate shuffling that occurred when Telmate took over as the communications provider for the Oregon Department of Corrections on July 1, 2012. Remember, this change does not have the clear price direction for all prisoners that the VIP change had. Instead, the phone rate changes left winners and losers depending on whether callers possessed a number with the same area code as the prison in question and the length of the call. Based on the price changes reported in Table 4.1, the fraction of calls we believe to be local (70% in 2012), and the average duration of calls (13 minutes under the new pricing scheme), we believe the price change represented a price decrease for the average prisoner.[26] In addition, total communications were much more limited during this period as neither messaging nor VIP chatting had been introduced. Prisoners were thus left with phone calls, mail, and in-person visitation as their only means of communicating with the outside world.

In Figure 4.4 we examine the impact of the price change on phone calls. Unfortunately, we have not been able to aquire prisoner-day level phone call data from before the price change. Instead, here we present annual calls per day from 2007 through 2015. Because the price change occurred in July of 2012, that year is split into two observations, pre and post change.

Figure 4.4 indicates that there was likely a discontinuous increase in calls following the price change. this is consistent with the overall impact of the change being a price decrease. Moreover, we observe strong positive trending after the price change, reversing a downward trend in calls that had been occuring in the years leading up to the change. It must be noted, however that we do not observe any information about call durations before July 1, 2012. It may be the

[26]The fact that 70% of calls were local in 2012 likely overstates the number of subsequent local calls. Once Tellmate took over, the price differentials between call distances fell dramatically. Many families had been purchasing cell phone with numbers local to the prison before the price change. After the change, we expect this practice to be significantly less common.

FIGURE 4.4. Phone Calls Before and After July 1, 2011



case that the switch to Telmate did not increase overall phone communication, but instead shifted communication to a pattern of more frequent, shorter calls.

In Figure 4.5 we show the short and long term impacts of the phone price change on total vitiation. Unlike the VIP price change, which was implemented immediately before a holiday season, the phone price change was implemented during a period in which seasonality is less likely to play a significant role. Given the significant day of the week effects that exist in visitation, all results have been demeaned by day of week. With or without this cleaning, we observe no evidence of a discontinuous change in visitation rates on either side of the price threshold. Similarly, long term trends appear relatively flat both before and after the change.

Table 4.8 reports the impact of the phone rate policy change for total, family, and friend visits. Each column is estimated using a specification similar to Equation 4.1. As in previous Tables, we restrict our analysis to a 100 day bandwidth to avoid conflating the impact of other communication policies with this one.

Across all types of visits, we find no evidence that the phone call price change affected visitation rates. Based on reported revenues and aggregate usage figures, we believe that the effect

FIGURE 4.5. Visitation Before and After July 1, 2011

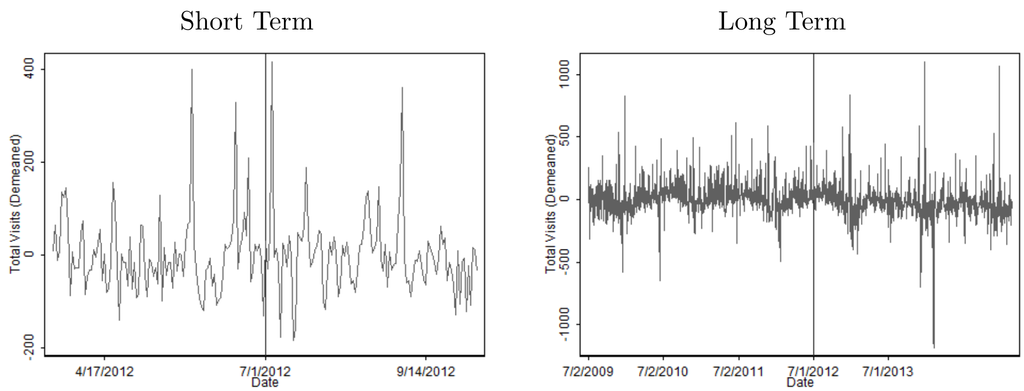


TABLE 4.8. Phone Price Change - Visitation

	Total Visits	Family Visits	Friend Visits
Treat (=1 if after 7/1/2012)	-0.00365	-0.00204	-0.00058
	(0.00295)	(0.00218)	(0.00057)
Date	0.01873*	0.01300	0.00294
	(0.01037)	(0.00866)	(0.00208)
Date^2	0.02152**	0.01438*	0.00400**
	(0.00890)	(0.00742)	(0.00182)
Date*Treat	-0.01342	-0.00920	-0.00378
	(0.01387)	(0.01156)	(0.00263)
Date^2*Treat	-0.02851***	-0.02080**	-0.00235
	(0.01093)	(0.00869)	(0.00307)
Weekend	0.08006***	0.05780***	0.01630***
	(0.00602)	(0.00465)	(0.00183)
Holiday	0.03301***	0.02166***	0.00877***
	(0.00151)	(0.00092)	(0.00103)
Observations	2,608,311	2,608,311	2,608,311
Mean	0.05252	0.03667	0.01164
Weather and Gas Price Controls	Yes	Yes	Yes
Prisoner Controls Yes	Yes	Yes	
Facility FE	Yes	Yes	Yes

Notes: * p $\leq$ 0.1, ** p $\leq$ 0.05, *** p $\leq$ 0.01. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth of the phone price change was to reduce prices for the average prisoner and increase total phone contact (number of calls multiplied by average call duration) significantly. If this is correct, these findings represent additional evidence of limited substitution effects between visitation and other forms of communication.

Introduction of VIP Services and Messaging

In addition to price changes, we can also consider whether the introduction of either messaging or VIP chatting influenced other forms of communication. In Figure 4.6, we present demeaned usage rates on the introduced technology before and after the introduction of messaging and the introduction of VIP chatting. In each case, we recenter observations within each facility to 0 on the day the technology was introduced and limit our analysis to a 100 day bandwidth on each side of the threshold. In terms of total usage, an average of 100 messages were sent and 70 messages were received each day in the 100 days following their introduction. VIP sessions were even less common, averaging only 40 instances per day.

Given the limited usage these techologies recieved when they were first introduced, we find no evidence of behavioral change among all prisoners conicident with their introduction. Here, we focus instead on a treatment on the treated analsysis considering only those prisoners that used the newly introduced technology within 100 days of its introduction. In Table 4.9 we estimate the impact of the introduction of messaging on other forms of communication while limiting our sample to a 100 day bandwith. As in earlier sections, we estimate a modified version of equation 4.1 with the introduction of messaging serving now as treatment.

We estimate positive coefficients on most types of communication but only our measure of total communication returns a statistically significant increase. This measure is designed to encompass how a prisoner's total number of contacts with the outside world changes with treatment. As such, messaging is included as part of the sum. As described above, in the first 100 days after introduction, prisoners averaged 170 messages per day. The coefficient on total

FIGURE 4.6. Communication Before and After the Introduction of Communication Technologies

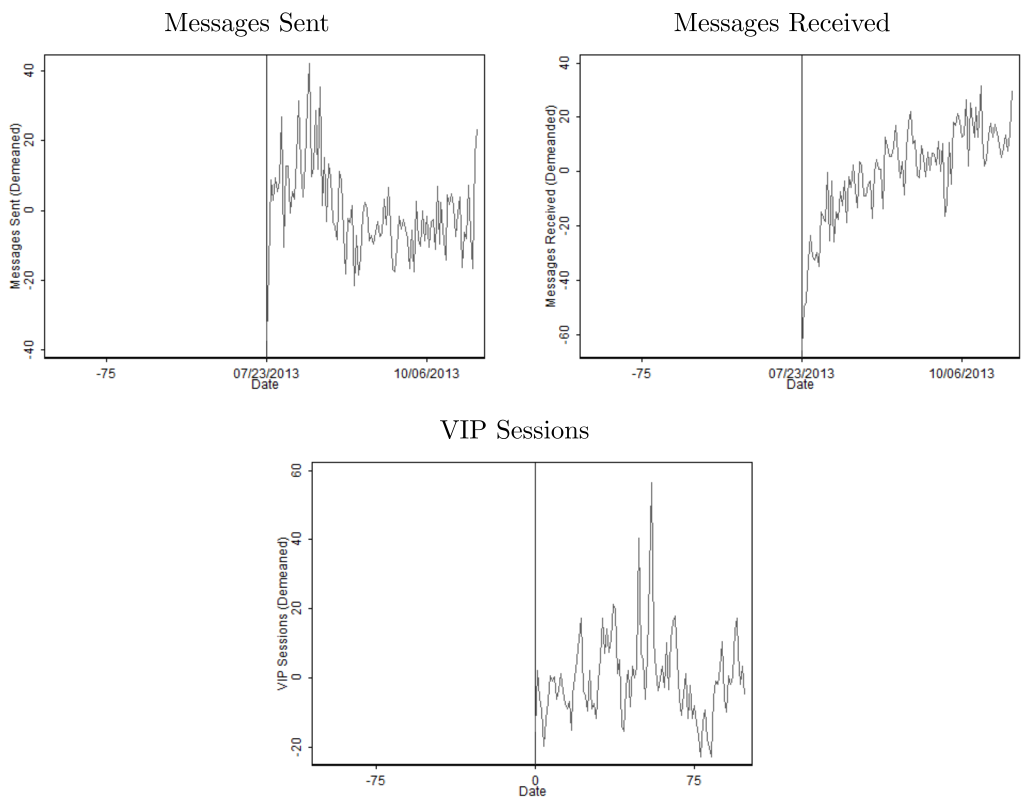


TABLE 4.9. Impact of Messaging Introduction on Other Forms of Communication

	(1) Total Visits	(2) Family Visits	(3) Friend Visits	(4) Calls	(5) VIP	(6) Total
Treat (=1 if after 11/1/2013)	0.00223	0.00223	0.00122	-0.02107	0.00183	0.04779**
	(0.00498)	(0.00363)	(0.00186)	(0.01845)	(0.00127)	(0.02063)
Date	-0.03331**	-0.03252**	-0.00244	0.12191*	-0.00132	0.08311
	(0.01656)	(0.01253)	(0.00583)	(0.06696)	(0.00484)	(0.07426)
Date^2	-0.03033**	-0.02925**	-0.00162	0.06163	-0.00016	0.03005
	(0.01465)	(0.01149)	(0.00582)	(0.04724)	(0.00482)	(0.05435)
Date*Treat	0.03479	0.03817**	-0.00231	-0.08669*	-0.00871	-0.02688
	(0.02543)	(0.01844)	(0.00847)	(0.04728)	(0.00530)	(0.05759)
Date^2*Treat	0.04592**	0.03779**	0.00948	-0.09165	0.00534	-0.04553
	(0.02122)	(0.01580)	(0.00768)	(0.06434)	(0.00583)	(0.07260)
Weekend	0.12612***	0.07214***	0.04854***	0.03297***	0.00788***	0.17468***
	(0.01120)	(0.00851)	(0.00363)	(0.01115)	(0.00225)	(0.01773)
Holiday	0.02314***	0.01078**	0.00955***	0.03489**	0.00650***	0.06280***
	(0.00558)	(0.00448)	(0.00111)	(0.01376)	(0.00202)	(0.01752)
Observations	290,091	290,091	290,091	290,091	290,091	290,091
Mean	0.06373	0.04248	0.01605	0.48077	0.00869	0.55322
Weather/Gas Price Controls	Yes	Yes	Yes	Yes	Yes	Yes
Prisoner Controls	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:** $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth and include only individuals who sent or received a message within 100 days of messaging becoming available. Messaging and VIP services were both introduced within the same week in TRCI because this makes it difficult to separately identify the impacts of each technology, TRCI has been excluded from these results. Each column has a unique dependent variable as indicated in the heading of that column. The dependent variable in column 6 is the sum of all forms of communication a prisoner can receive that we observe. Specifications are consistent with column 4 of Table 4.5]

communication we estimate in Table 4.9 suggests an increase in communication of only 69 contacts per day. The difference appears to be driven by a decrease in phone use which, while not statistically significant, suggests that phone calls fell by 4% after the introduction of messaging. Thus, while the overall effect on communication is positive, we find some evidence that subsitution is occuring bewtween phoone calls and messaging.

As a final policy change, we consider the impact of introducing VIP services into a prison. Unlike the other policy changes, VIP services were rolled out gradually across facilities over the course of a full year. Because of this gradual roll-out, VIP introductions occur both before and after the introduction of messaging and before and after VIP prices were reduced. While we have considered the impact on each group of facilities individually, in Table 4.10 we present the aggregate results, recentering each facility on the date VIP chatting was introduced. Beacuse most facilities saw the introduction of VIP services before the introduction messaging, we can estimate

TABLE 4.10. Impact of VIP Introduction on Other Forms of Communication

	(1) Total Visits	(2) Family Visits	(3) Friend Visits	(4) Calls
Treat (=1 if after 11/1/2013)	-0.00300	0.00186	-0.00392	0.02150**
	(0.00812)	(0.00564)	(0.00272)	(0.00936)
Date	0.03267	-0.00124	0.02253**	0.03588
	(0.02106)	(0.01470)	(0.00972)	(0.02983)
Date^2	0.03722*	0.00869	0.01692*	0.04890*
	(0.02003)	(0.01427)	(0.00905)	(0.02752)
Date*Treat	-0.02316	0.00618	-0.02007	-0.03350
	(0.03757)	(0.02629)	(0.01429)	(0.04575)
Date^2*Treat	-0.06119*	-0.02138	-0.02254*	-0.05951
	(0.03423)	(0.02499)	(0.01298)	(0.04277)
Weekend	0.17643***	0.12105***	0.03310***	0.08914***
	(0.01771)	(0.01295)	(0.00556)	(0.01365)
Holiday	0.07620***	0.04773***	0.02040***	0.06722***
	(0.01091)	(0.00741)	(0.00347)	(0.01774)
Observations	170,420	170,420	170,420	170,420
Mean	0.10252	0.06418	0.02906	0.52478
Weather/Gas Price Controls	Yes	Yes	Yes	Yes
Prisoner Controls	Yes	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes

*Notes:** $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Standard errors allow for clustering by date and are reported in parenthesis. Date variables are scaled to represent the estimated effect after 100 days. Results based on a 100 day bandwidth and include only individuals who sent or received a message within 100 days of messaging becoming available. Messaging and VIP services were both introduced within the same week in TRCI because this makes it difficult to separately identify the impacts of each technology, TRCI has been excluded from these results. Each column has a unique dependent variable as indicated in the heading of that column. Specifications are consistent with column 4 of Table 4.5

the impact of the introduction of VIP services on messaging use. Instead, in Table 4.10 we focus only on visitation and phone calls.

Consistent with the VIP price decrease, the introducion of VIP chatting does not appear to have led to significant decreases in other types of communication. We do, however, find a statistically significant increase in phone calls. Because messaging was not widely available at the time of VIP introduction, the increase in phone calls we observe here may again be indicative of prisoners attempting to coordinate VIP sessions with friends and family. The coefficient point estiamte suggests that the 852 prisoners in this subsample made 4.1% or 18 more phone calls per day.

Heterogeneity

While we find very limited evidence of any substitution effects among types of communication overall, it may be the case that looking at the whole population masks important heterogeneity. For example, rural prisons may find VIP services to be a more appealing substitute for visitation because visitation becomes more costly as distance increases. In Table 4.11 we list the total number of non-zero observations for each type of communication as well as for the entire sample. In subsequent columns, we indicate the fraction of those observations that are made up of prisoners with the indicated trait. The table thus indicates which groups are using a disproportionate amount of the various communication technologies. We include only the final year of our data, March 1, 2014 - February 28, 2015, so that all policy change had already occurred and VIP and messaging services had been introduced across all facilities.

In Panel A, we consider heterogeneity by age. Prisoners 43 and under make up 72% of the sample and all appear to have similar usage patterns across communication technologies. Older prisoners, on the other hand, are under represented in all forms of communication. This drop off is likely a function of these prisoners spending much of their lives in prison. This would both limit their exposure to technology, potentially increasing the costs of adopting new forms of communication, and limit the number of frinds and relatives they maintain close ties with.

Gender differences are considered in Panel B. Female prisoners are far more communicative and are over represented in every measure of communication. None the less, there is gender variation in preferred communication methods with women relatively more likely to choose in-person visitation and messaging while men are more likely to choose phone calls or VIP chatting.

More significant differences appear in Panel C where we consider heterogeneity based on prison location. Despite accounting for nearly 60% of all prisoners, urban prisons are the site of only 33% of VIP sessions and account for less than 50% of all messages and phone calls. On the other hand, Urban prisons are over represented for visitation. This suggests that there are real substitution effects between communication types and that the high cost of visiting prisoners incarcerated in rural areas is a significant deterrent. This variation also indicates that urban and rural prisons may have very different responses to treatment.

TABLE 4.11. Usage Rates By Age, Prison Location, and Gender

Panel A: Age	**Non-0 Obs.**	**Age < 27**	**Age 27-33**	**Age 34-43**	**Age > 43**
Total Observations	5,799,776	0.231	0.224	0.246	0.277
VIP Services	39,621	0.281	0.341	0.251	0.106
Messages Sent	121,644	0.204	0.286	0.322	0.163
Messages Received	118,700	0.228	0.305	0.309	0.136
Phone Calls Made	1,950,833	0.258	0.271	0.251	0.201
Total Visits	255,839	0.276	0.270	0.254	0.183
Family Visits	189,294	0.285	0.269	0.254	0.176
Friend Visits	66,545	0.278	0.276	0.250	0.178
Panel B: Gender	**Non-0 Obs.**	**Male**		**Female**	
Total Observations	5,799,776	0.910		0.090	
VIP Services	39,621	0.879		0.121	
Messages Sent	121,644	0.840		0.160	
Messages Received	118,700	0.853		0.147	
Phone Calls Made	1,950,833	0.880		0.120	
Total Visits	255,839	0.844		0.156	
Family Visits	189,294	0.847		0.153	
Friend Visits	66,545	0.840		0.160	
Panel C: Location	**Non-0 Obs.**	**Urban**		**Rural**	
Total Observations	5,799,776	0.581		0.419	
VIP Services	39,621	0.326		0.674	
Messages Sent	121,644	0.441		0.559	
Messages Received	118,700	0.437		0.562	
Phone Calls Made	1,950,833	0.455		0.540	
Total Visits	255,839	0.644		0.356	
Family Visits	189,294	0.624		0.375	
Friend Visits	66,545	0.683		0.317	

Notes: Includes final year of observations, March 1, 2014 through February 28, 2015. Each decimal observation represents the fraction of all non-zero observations of the indicated communication mechanism that can be attributed to the group displayed in that column.

We consider each communication measure for urban and rural prisons separately in Table 4.12. In particular, each row in Table 4.12 indicates the dependent variable considered in that specification while columns indicate which group was included in the sample. Each cell thus displays the point estimate and standard error on our treatment variable based on our preferred specification (Equation 4.1).

By splitting the data between urban and rural prisons, we are able to observe real substitution effects taking place between visitation and phone calls when phone call prices were reduced. In addition to the increased costs of visitation at rural prisons (due largely to the increased travel distance), family members of rural prisoners are less likely to have local numbers than the families of prisoners in urban prisons. This implies that in rural prisons, the price change was likely a more clear price decrease. In terms of magnitude, the average prisoner in a rural prison could expect to recieve 13 visits each year before the price change and 11 visits per year after the price change.

Conclusion

Due to the exceptionally high rate of incarceration in the United States and increased usage of prison as a crime reduction policy tool, policies which reduce the criminogenic effects of prison may yield long-term benefits to society via reduced recidivism and lower inter-generational transmissions of criminality. In this paper we study the effect of substantial decreases in the costs of communication with inmates through reduced prices for video chatting. Overall we find no evidence that visitation is affected by these changes and weak evidence that other forms of communication actually increase. The lack of significant change, particularly in in-person visitation, challenge the conventional wisdom about the impacts of technology based communication advancements in prison systems which suggest that substitution effects will cause reductions in visitation (Stroud and Brustein, 2015).

TABLE 4.12. Heterogeneity -Price Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	Phone Price Change		**VIP Price Change**			
	All Prisoners	Phone Users	All Prisoners	Phone Users	VIP Users	VIP Early
Panel A: Urban Prisons						
Total Visits	-0.00002	0.00009	0.00336	0.00415	0.00742	0.01005
	(0.00385)	(0.00433)	(0.00713)	(0.00782)	(0.01118)	(0.01775)
Family Visits	0.00050	0.00056	0.00220	0.00275	0.00642	0.01227
	(0.00298)	(0.00342)	(0.00511)	(0.00560)	(0.00754)	(0.01085)
Friend Visits	0.00015	0.00032	0.0126	0.00150	0.00138	-0.00010
	(0.00112)	(0.00126)	(0.00185)	(0.00202)	(0.00396)	(0.00730)
All Communication			-0.00082	0.00071	0.01035	0.02527
			(0.01318)	(0.01444)	(0.01962)	(0.02721)
Phone Calls			-0.00636	-0.00581	0.00048	0.01255
			(0.00744)	(0.00816)	(0.00942)	(0.00998)
Call Duration			0.00249	0.01518	0.04916	0.07423
			(0.09299)	(0.10137)	(0.14770)	(0.19426)
Messages Sent			0.00163**	0.0079**	0.00224	0.00008
			(0.00075)	(0.00081)	(0.00195)	(0.00398)
Messages Received			0.00014	0.00013	-0.00102	-0.00162
			(0.00059)	(0.00065)	(0.00157)	(0.00335)
VIP Sessions			0.00041	0.00045	0.00123	0.00419
			(0.00118)	(0.00128)	(0.00339)	(0.00585)
Observations	1,065,665	898,689	575,689	528,436	194,231	79,286
Panel B: Rural Prisons						
Total Visits	-0.00644**	-0.00681**	0.00230	0.00237	0.00473	0.00445
	(0.00303)	(0.00342)	(0.00345)	(0.00371)	(0.00550)	(0.00716)
Family Visits	-0.00392*	-0.00407*	0.00128	0.00132	0.00339	0.00486
	(0.00205)	(0.00229)	(0.00269)	(0.00289)	(0.00405)	(0.00528)
Friend Visits	-0.00120	-0.00129	0.00036	0.00038	0.00042	-0.00107
	(0.00077)	(0.00089)	(0.00067)	(0.00072)	(0.00137)	(0.00180)
All Communication			-0.00574	-0.00667	0.00257	0.00049
			(0.00999)	(0.01073)	(0.01427)	(0.01566)
Phone Calls			-0.01201	-0.01327	-0.01261	-0.02239**
			(0.00756)	(0.00814)	(0.00977)	(0.00927)
Call Duration			-0.09657	-0.10826	-0.07957	-0.29949*
			(0.10072)	(0.10839)	(0.14330)	(0.015673)
Messages Sent			0.00203***	0.00219***	0.00519***	0.00771***
			(0.00051)	(0.00056)	(0.00122)	(0.00188)
Messages Received			0.00090**	0.00093**	0.00224**	0.00410***
			(0.00041)	(0.00043)	(0.00097)	(0.00145)
VIP Sessions			0.00104	0.00111	0.00302	0.00662
			(0.00117)	(0.00125)	(0.00307)	(0.00449)
Observations	1,542,445	1,385,820	1,544,143	1,433,284	579,577	281,043

*Notes:** p ≤ 0.1, ** p ≤ 0.05, *** p ≤ 0.01. Each cell indicates the results from our preferred specification for the indicated group of prisoners. The VIP Early column includes only prisoners using VIP services at least once before the price decrease on November 1, 2011 occurred. Prisoners incarcerated in OSP or OSCI, which did not introduce VIP sessions until after the price change, are not included in columns 3-6. Dependent variables are listed in the row titles. Standard errors allow for clustering at the prisoner level and are reported in parenthesis. Results based on a 100 day bandwidth.

We also consider the impact of a telephone price reshuffling that likely increased costs among the most frequent prisoner-caller pairs. Again, we find no impact of the price change on visitation overall although there is some evidence of substituiton away from visitation where in-person visitation is most costly. If previous studies are correct in their assertion that increased communication lead to reduced recidivism for prisoners, our results suggest that reducing the price of communication technologies has the potential to significantly reduce the criminogenic effect of prison.

In future work, we intend to assess the impact of these communication changes on in-prison misconducts. We are particularly interested in violent misconducts and drug misconducts, the latter of which may be directly tied to visitation rates as in-person visitation is widely recognized to be a key pipeline through which drugs enter the prison system. Notably, while both of these outcomes are used to measure short-run changes in prisoner behavior, they are also both strong predictors of future recidivism and criminality (French and Gendreau, 2006; Cochran, Mears, Bales, and Stewart, 2012; Dooley, Seals, and Skarbek, 2014). By understanding the impact of communication technology on communication use, misconducts, and recidivism, we will be able to fully understand the impacts of communication technologies and offer clear policy suggestions to the many correctional departments currently considering how and whether to embrace the technological advancements that can reduce the separation between prisoners and the outside world.

CHAPTER V

CONCLUSION

Using both theoretical and empirical techniques, in this dissertation I provide insight into a number of pressing questions facing policy makers.

In Chapter II, co-authored with Glen R. Waddell, I expand and improve upon current modeling of the labor market by offering a hiring process in which the candidate is evaluated sequentially by two agents of the firm who each observe an independent signal of the candidate's productivity. The model's inclusion of taste-based discrimination allows for important policy insights into programs like Affirmative Action that encourage diversity but often only provide incentives to decision makers who will fall late in the sequential hiring process. The key insight is that the agent with a smaller value for the non-productive attribute will work to offset the other agent's discriminatory actions. The offsetting behavior can be large enough to cause a highly-productive candidate who offers a non-productive trait valued by one agent to be less likely to be hired than a candidate without the valued trait even when the other agent has no preference over non-productive attributes. This suggests that improperly aligning incentives throughout the hierarchy of the firm can lead to detrimental outcomes for both the firm and it's potential employees.

I go on to demonstrate, along with Benjamin Hansen and Glen R. Waddell, that prisoners do not respond to increased behavioral incentives stemming from more generous sentence reduction policies nor does their behavior change with the varying incentives presented by the systematic six-month reviews cycles employed by the prison to award these sentence reductions. On the other hand, inmates improve their behavior disproportionately in the days immediately prior to and following an assessment. More frequent reviews appears to be a more effective policy prescription to reduce misconducts than simply changing the rate at which prisoners earn sentence reductions which has been the more popular choice among policy makers.

Finally, in work co-authored with Benjamin Hansen and Glen R. Waddell, I find that the Oregon Department of Correction's expansion of outside communication opportunities for prisoners have not led to an overall reduction in in-person visitation. We find significant heterogeneity by prison location with prisons farther from population centers experiencing a mild substitution effect as opportunities for non-visitation based communication increase. For prisons in urban areas, on the other hand, we find suggestive evidence that visitation increases as the opportunities for technology based communication are improved. Overall, the evidence suggests further expansions to the communication system and encouragement of its use may lead to widespread increases in the connections between prisoners and the outside world.

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